Radio resource allocation algorithms for energy efficient cellular networks powered by renewable energy and smart grid

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Résumé

1. Contexte et motivation du travail effectué :

L'Internet est l'une des principales infrastructures créées dans les dernières années. Les utilisateurs de cette infrastructure sont capables d'utiliser un vaste choix de services tels que le multimédia, les jeux, la navigation, etc. Cependant, avec sa popularité croissante et le trafic de données de plus en plus important, l’empreinte énergétique d’Internet devient un facteur important à considérer [1]. Par exemple, [2] a estimé en 2007 que le secteur des Technologie de l’Information et des Communications est responsable de 2% des émissions mondiales de CO2, autant que le transport aérien. Cependant, contrairement au trafic aérien, le trafic d’usagers de ce secteur augmente de façon exponentielle et devient insoutenable à long terme.
Une des façons les plus fréquentes d'accès à l'Internet se fait via la communication sans fil cellulaire, qui consomme plus de 0,5% de l'approvisionnement mondial en énergie [3]. Ce pourcentage augmentera encore plus avec la croissance drastique de la demande des usagers. Basé sur l’indice des réseaux visuels de Cisco (Cisco Visual Networking Index) [4], le trafic de données mobiles devrait croître de 61% par an pour atteindra en 2018 une augmentation de 11 fois par rapport à celui en 2013. Par conséquent, les opérateurs ont besoin de réagir rapidement à cette croissance extrême en ce qui concerne la demande de la capacité et de la consommation d'énergie. Cette dernière est d'une importance croissante étant donné que l'énergie et les coûts de carburant peuvent atteindre plus de 32% des dépenses opérationnelles dans certains cas [5].

La principale orientation de recherche et développement pour les ingénieurs et les chercheurs est d'améliorer l'efficacité énergétique des réseaux mobiles. L'Efficacité Energétique a été adoptée pour être l'un des concepts majeurs dans la conception et l'exploitation des réseaux mobiles, où plusieurs techniques complémentaires sont employées pour l’atteindre [6]. Ils comprennent la gestion des ressources radio, l’extinction de stations de base, le déploiement hétérogène, la radio cognitive, etc. En outre, une nouvelle direction a émergé, où les opérateurs de réseaux mobiles considèrent explicitement les sources d'énergie et les coûts économiques et

environnementaux liés [7].

Tenant compte du fait que les stations de base sont le consommateur majeur de l'énergie dans un réseau mobile, avec 75 à 80% de la consommation totale du réseau [8], leur alimentation avec des sources d'énergie renouvelable a le potentiel de devenir un outil indispensable pour les opérateurs de réseaux mobiles. En conséquence, la durabilité énergétique (en anglais, sustainability) apparaît comme un concept essentiel, et pose une nouvelle question: comment utiliser l'énergie récoltée pour répondre à la demande de trafic, tout en répondant aux exigences de qualité de service des utilisateurs finaux? En fait, l'efficacité énergétique et l'énergie verte sont promises toutes les deux à faire partie de futures technologies mobiles. Plus précisément, l'ère 5G sera témoin de l'augmentation de l'importance de réduction des coûts opérationnels, des déploiements de l'énergie renouvelable et des réseaux plus efficaces et durables en terme d'énergie [9]. À cet égard, plusieurs projets ont été développés tels Mobile Radio Networks (OPERA-NET 1 and 2) [10], Energy Aware Radio and Network Technologies (EARTH) [11], Towards Real Energy-efficient Network Design (TREND) [12] et GreenTouch [13]. En ce qui nous concerne, notre travail est développé dans le cadre du projet européen Celtic Opera Net 2 avec de nombreux partenaires tels que Orange, Thomson Broadcast, Nokia, Alcatel-Lucent, etc.

Une voie prometteuse pour répondre à l'augmentation de la demande énergétique des réseaux mobiles est l'utilisation des sources d'énergie renouvelable pour alimenter les stations de base. Une des justifications instinctives et populaires de l'utilisation de l'énergie renouvelable est le désir de rendre notre société plus écologique, en diminuant par exemple les émissions mondiales de gaz à effet de serre. En plus de la diminution des émissions de gaz à effet de serre, l'énergie renouvelable est une solution à de nombreux autres problèmes. Par exemple, l'utilisation de l'énergie renouvelable est proposée comme solution dans les zones où il n'y a pas de réseau électrique telles que les îles et les déserts [1]. Elle résout également le problème des endroits où il est difficile ou impossible d'obtenir une connectivité au réseau électrique. Jusqu'à présent, les opérateurs mobiles utilisent des générateurs électriques diesel pour faire fonctionner les stations de base comme solution pour la plupart de ces cas, ce qui est non seulement une solution coûteuse en raison de son prix et de transport [14], mais aussi l'une des sources d'énergie les plus polluantes. Un programme appelé Green Power for Mobile a été lancé par l'Association GSM pour aider l'industrie de la téléphonie mobile à déployer diverses sources d'énergie renouvelable pour alimenter 640 000 stations de base nouvelles ou déjà existantes non connectés au réseau électrique [15]. Cette action permettrait d'économiser environ 0,35% de la consommation mondiale de diesel. En outre, l'énergie renouvelable peut également faire partie de la solution pour pallier à une éventuelle défaillance dans le réseau électrique [16] et la conséquence de cet échec sur la communication, où 65% des interruptions de communication sont dues aux défaillances d'alimentation et 85% d'eux sont découverts après plus de 12 heures, principalement en raison de plaintes d'utilisateurs [17]. L'utilisation de l'énergie renouvelable dans ce cas a un sens commercial pour les opérateurs de réseaux mobiles en soutenant la durabilité et rentabilité des entreprises.

Dans [18], les auteurs étudient le rôle des énergies renouvelables dans la réduction du déploiement et des coûts d'opération des réseaux cellulaires de prochaine génération. Leur étude montre qu'il est économiquement approprié et respectueux pour l'environnement d'utiliser des sources d'énergie renouvelables dans l'alimentation de stations de base de petites cellules (small cells), et que ces ressources peuvent servir de base pour de nouveaux modèles d'affaires. Un exemple de ces modèles serait l'introduction de nouvelles réglementations du spectre pour licencier des opérateurs mobiles tenus de ne pas dépasser un certain pourcentage de fonctionnement à puissance maximale du réseau ou de limite supérieure de libération d'émissions de carbone. Enfin, l'énergie renouvelable peut être considérée comme une source de revenus par les opérateurs. Cela peut être réalisé, par exemple, en vendant le surplus d'énergie au réseau électrique, ce qui est un cas d'utilisation particulièrement intéressant pour les pays développés avec des marchés d'énergie matures. En outre, le développement dans les technologies d'énergie renouvelable améliore l'efficacité de la production d'électricité, et aboutit à la diminution du coût de déploiement d'un système d'énergie verte. Par exemple, le rendement énergétique des cellules solaires à augmenté jusqu'à plus de 41%, ce qui est plus du double de l'efficacité de ceux qui sont actuellement déployés, selon [19].

En plus de son importance écologique, l'introduction de l'énergie renouvelable dans l'alimentation des stations de base cellulaires a une importance économique pour l'opérateur sans fil, pour qui elle ouvre des opportunités pour de nouveaux modèles d'affaires. Il est donc important d'étudier le sujet afin de déterminer les gains potentiels, les scénarios d'applicabilité, les stratégies de déploiement et des nouvelles architectures de système.

Dans le secteur de l'énergie, des efforts importants ont été dépensés pour l'évolution du réseau électrique en un réseau plus intelligent, la Smart Grid [20]. La vision ultime est d'avoir un réseau électrique global, qui comporte tous les appareils électriques et permet la communication bidirectionnelle eux. La Smart Grid sera en mesure de réduire la consommation d'énergie et les émissions de carbone et fournit aux clients des services plus fiables. Les réseaux mobiles peuvent être considérés comme des charges d'énergie géographiquement distribuées. Avec les fonctionnalités avancées de

Smart Grid, il est obligatoire qu'elle soit considérée en étudiant le comportement énergétique des réseaux mobiles liés au réseau électrique.

Alimenter les stations de base avec des sources d'énergie renouvelables est une direction prometteuse dans le contexte des réseaux mobiles. Cependant, il n'est pas trivial de concevoir ou exploiter tels réseaux. En plus de la gestion des ressources radio, l'optimisation des réseaux mobiles verts implique l'optimisation de l'utilisation de l'énergie renouvelable produite. En outre, tenir en compte de l'environnement Smart Grid (réseau électrique intelligent) fournit de nouveaux problèmes et introduit de nouveaux défis de recherche. Cette thèse vise à contribuer dans le domaine des techniques dans les réseaux mobiles alimentés par des sources d'énergie renouvelables et par le réseau électrique du type Smart Grid.

2. Description de notre travail

Le travail effectué a examiné les diverses tendances existant dans la littérature de « Green Wireless » (réseaux sans fil verts) pour avoir une bonne connaissance des études existantes et pour détecter et exploiter les approches possibles. Après une étude exhaustive de l'état de l'art, nous avons choisi de considérer le problème consistant à minimiser le coût opérationnel de l'énergie des réseaux mobiles alimentés par des sources d'énergie renouvelables, en tenant compte de l'environnement Smart Grid. D'une part, l'augmentation du coût opérationnel de l'énergie des opérateurs mobiles est l'une des principales préoccupations des opérateurs de réseaux mobiles. D'autre part, cela contribuera à la diminution des émissions de gaz à effet de serre sachant qu'un grand nombre de pays ont déjà inclus des taxes d'émission de carbone, explicitement ou implicitement, dans les prix de l'énergie [21].

Nous avons commencé par identifier les principales approches proposées et connaître les avantages et les inconvénients de chaque technique et mécanisme. Plus spécifiquement, notre étude des réseaux mobiles alimentés par des sources d'énergie renouvelables nous a permis de déterminer les problèmes non résolus sur ce domaine. À cet égard, nous avons proposé une nouvelle classification des axes de recherche, un modèle pour les stations de base d'énergies renouvelables et un cadre pour les techniques et mécanismes. Cela nous a permis de cibler notre axe de recherche vers les stations de base alimentées par l'énergie renouvelable et par le réseau électrique du type Smart Grid.

Notre deuxième étape a été la classification des scénarios et objectifs de l'utilisation de l'énergie renouvelable dans l'alimentation des stations de base liés au réseau électrique Smart Grid. Cette étape a élargi la possibilité d'utiliser l'énergie renouvelable par les opérateurs de réseaux mobiles. En se concentrant sur la réduction du coût opérationnel de l'énergie, nous étudions d'abord la gestion de l’énergie dans les stations de base. Nous proposons un nouvel algorithme déterminant l'utilisation des énergies renouvelables basé sur le prix dynamique de l'énergie fournie par le Smart Grid et de l'état du stockage de l'énergie. Les résultats montrent que les objectifs de minimiser le coût opérationnel de l'énergie et l’énergie sur-réseau sont corrélés, mais pas identiques. En outre, les résultats ont permis de vérifier qu’on doit mieux utiliser l’énergie renouvelable pour une bonne stratégie d’ensemble d’utilisation de l'énergie renouvelable.

Dans le prolongement de travaux antérieurs, nous avons étudié le problème de minimiser le coût opérationnel de l'énergie d'un réseau de stations de base du type dit Macro. Nous proposons un nouvel algorithme qui vise à assigner l'énergie renouvelable, éteindre temporairement les stations de base, ajuster la puissance transmise et déterminer le nombre de blocs de ressources actives. Les résultats montrent que la coopération entre les stations de base peut augmenter la réduction des coûts, et que notre algorithme donne de meilleurs résultats que les algorithmes existants. Nous avons également montré qu’une réduction de coûts supplémentaire peut être obtenue en ajoutant de petites cellules alimentées par énergie renouvelable.

Ensuite, nous étudions la couverture, la capacité et les performances d'un réseau cellulaire réel d'un opérateur européen. Nous proposons deux algorithmes qui visent à réduire la consommation d'énergie et les coûts opérationnels de l'énergie respectivement. Nous proposons également un nouveau concept: Advance Sizing du système d'énergie renouvelable. Advance Sizing correspond au dimensionnement de la taille des sources d'énergie renouvelables et du stockage de l'énergie, basé sur le fonctionnement du réseau. Les résultats montrent qu'il est possible de réduire le coût opérationnel de l'énergie du réseau jusqu'à 51% en utilisant des sources d'énergie renouvelables qui produisent 20% de la demande du réseau, pour certaines configurations.

Enfin, nous proposons une nouvelle architecture d'intégration du réseaux mobiles et du Smart Grid basée sur la perspective de l’un par rapport à l’autre. Comme application de cette architecture, nous étudions un nouveau comportement de stations de base alimenté par énergie renouvelable pour lesquels on fournit des services auxiliaires (ancillary services) à la Smart Grid. A notre connaissance, nous sommes les premiers à proposer ce concept dans le fonctionnement des stations de base. Les résultats montrent que cette approche conduit à des coûts opérationnels de l'énergie négative où le Smart Grid paie à l'opérateur de réseau mobile, si le dispositif réseau mobile –

stockage d’énergie – énergie renouvelable – Smart Grid est bien dimensionné, et pour certaines configurations.

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Abstract

Powering cellular base stations with renewable energy sources has emerged as a sustainable solution to the increase of the network energy consumption. The latter is of great importance, where energy cost represents significant portion of the total operational cost. The objective of this thesis is to contribute into the development of renewable energy-powered cellular networks. Our work was done taking as reference framework the current and future trends in green mobile and cellular technologies. Moreover, the evolution of the power grid into the Smart Grid imposes itself in the core of our work.

First, we start by classifying the existing work into research sectors. We integrate the utilized tools and techniques in a new framework. The framework is composed of layers, where each of the layers works at a specific scale. In the energy efficiency layers, the techniques begin with component enhancement passing through environment learning, radio resource management and heterogeneous deployment up to cell layout adaptation mechanisms. The renewable energy layers consists of component enhancement, environment learning and energy management. This integration allowed us to leverage the interaction between multiple approaches. In this thesis, we focus specifically on the energy management and the upper layers of energy efficiency. Our choice was motivated by the importance of the utilization of renewable energy and the important savings that can be obtained.

Second, we propose a new methodology to identify the case studies of on-grid cellular networks powered by renewable energy sources. The methodology starts by examining the area configuration and determining the objectives of using renewable energy. The chosen objective determines the definition of renewable energy utilization. Thus, we present some of the objectives found in literature and extend them by proposing new ones. Moreover, we classify the constraints of the problem that should be considered to have more realistic study.

Throughout this work, we consider the problem of minimizing the energy operational cost in rare power grid failure areas. We present the main energy dynamic tariff programs. By considering base stations distributively operating in a variable on-grid energy price environment, we use energy management to minimize their energy operational cost. We propose a simple price aware energy management algorithm that determines the usage of renewable energy based on on-grid energy price and storage level. On one hand, results verify that minimizing the on-grid energy and the energy operational cost are correlated but not identical. On the other hand, we validate the importance of considering energy management when operating base stations powered by the grid and renewable energy.

Afterwards, we highlight the importance of cooperation between base stations powered by renewable energy and the power grid. We study the performance of a network of macro-base stations combining energy management with radio resource management and cell lay-out adaptation to further increase the saving in the energy operational cost. We formulate the problem of minimizing the energy operational cost of the network and propose a new algorithm that allocates renewable energy, switches-off base stations, adjusts the transmitted power and determines the number of activated resource blocks. Results show that cooperation between base stations can extend the cost savings of using renewable energy sources. Then, we study the effect of adding small cells powered solely by renewable energy. Results show that further cost reduction can be achieved in this case.

Later in our discussion, we analyse the usage of renewable energy in a realistic scenario. Based on real measurement of a European mobile network operator in a major European city, we study the effect of energy management and base station switching-off on the on-grid energy consumption and energy cost. We analyze the coverage and capacity of the network and present the effect of traffic variation on the power demand. Then, we propose two algorithms that aim at minimizing the on-grid energy consumption and energy cost respectively. By analyzing the variants of each algorithm, we were able to identify some recommendations for renewable energy sources and energy storage dimensioning process. Moreover, we find that it is possible to reduce 51% of the energy cost by using renewable energy that produce only 20% of the network energy demand.

Finally, we propose new integration architecture for the cellular networks and the Smart Grid. The architecture is constructed based on the mutual views between the Smart Grid and the cellular network and aims at facilitating the interaction between them. Then, we study a new energy behaviour of the renewable energy powered base station, where it provides ancillary services to the Smart Grid. Based on the integration architecture, we propose an aggregator-based architecture for base stations interacting with the Smart Grid. After formulating the problem, we propose a new algorithm that manages the energy storage and exploits the concept of delay tolerant users to reduce the energy operational cost. Results show that providing ancillary services may lead to negative operational cost when suitable radio resource allocation scheme and effective renewable energy management are used.

Contents

Thesis Publications

- Hussein Al Haj Hassan, Loutfi Nuaymi, and Alexander Pelov. ”Renewable energy in cellular networks: a survey.” Online Conference on Green Communications (GreenCom), 2013 IEEE. IEEE, 2013.
- Hussein Al Haj Hassan, Loutfi Nuaymi, and Alexander Pelov. ”Classification of renewable energy scenarios and objectives for cellular networks.” Personal Indoor and Mobile Radio Communications (PIMRC), 2013 IEEE 24th International Symposium on. IEEE, 2013.
- Hussein Al Haj Hassan, Alexander Pelov, and Loutfi Nuaymi. ”Cost-efficient radio resource allocation in hybrid energy cellular networks.” Global Communications Conference (GLOBECOM), 2014 IEEE. IEEE, 2014.
- Hussein Al Haj Hassan, Arshad Ali, Loutfi Nuaymi, Salah Eddine Elayoubi, ”Renewable Energy Usage in the Context of Energy-Efficient Mobile Networks.” Vehicular Technology Conference (VTC Spring), 2015 IEEE 81 th. IEEE, 2015.
- Hussein Al Haj Hassan, Samantha Gamboa, Loutfi Nuaymi, Alexander Pelov, Nicolas Montavont, ”The Smart Grid and Future Mobile Networks: Integrating Renewable Energy Sources and Delay Tolerant Users” Vehicular Technology Conference (VTC Fall), 2015 IEEE 82 th. IEEE, 2015.
- Hussein Al Haj Hassan, Alexander Pelov, and Loutfi Nuaymi. ”Integrating Cellular Networks, Smart Grid and Renewable Energy: Analysis, Architecture and Research Challenges”, IEEE Access journal, 2015.

List of Acronyms

3GPP 3rd Generation Partnership Project

BS Base Station

CapEx Capital Expenditure

CoMP Coordinated Multipoint

CPP Critical Peak Pricing

CSO Cell Size Optimizing

CSRA Coverage Supply Redundancy Architecture

DP Dynamic programming

DTU Delay Tolerant Users

EBR electric bill reduction algorithm

ECU energy control unit

EDRs Energy Depletion Rates

GHG Greenhouse Gas

HetNet Heterogeneous Network

ICE Intelligent Cell Breathing

ICT Information and Communication Technology

LTE Long Term Evolution

MEA Multi-stage Energy Allocation

MEC Minimizing Energy Consumption

MNO Mobile Network Operator

OpEx Operational Expenditure

PV Photovoltaic

QoS Quality of Service

RE Renewable Energy

REBS Renewable Energy Base Station

RES Renewable Energy Source

RGFA Rare Grid Failures Areas

RRM Radio Resource Management

RTE Réseau de transport d électricité, France Electricity Transmission Network

RTP Real Time Pricing

SG Smart Grid

SGFA Systematic Grid Failures Areas

SGO Smart Grid Operator

SPAEMA Simple Price-Aware Electricity Management Algorithm

SSF Strongest Signal First

TOU Time Of Use

CHAPTER 1 Introduction

1.1 General background

The Internet is one of the major infrastructures created in the past decades. Users of this infrastructure are able to use vast range of services such as multimedia, gaming, browsing, etc. However, with its growing popularity and ever increasing data traffic, its energy and Carbon footprint becomes an important factor to be considered [1]. For example, [2] estimates that Information and Communication Technology (ICT) sector is responsible for 2% of the global CO_2 emissions in 2007, as much as the air transportation. However, in contrast to air traffic, ICT energy consumption increases exponentially, which is unsustainable in the long run.

One of the main ways to access the Internet is via cellular communication, which consumes more than 0.5% of the global energy supply [3], a number bounded to increase even further with the drastic growth of users demands. Based on Cisco Visual Networking Index [4], mobile data traffic is expected to grow 61% per year, so that it will reach by 2018 a 11-fold increase over 2013. Therefore, telecom operators need to react rapidly to this extreme growth in terms of capacity demand and energy consumption. The latter is of increasing importance considering that energy and fuel cost can reach more than 32% of the operational expenditure [5].

The main line of research and development followed by engineers and researchers is to enhance the efficiency of mobile networks[1]. *Energy Efficiency* was adopted to be one of the major concepts in designing and operating mobile networks, where multiple complementary techniques are employed to improve it [6]. They include radio resource management, cell layout adaptation, heterogeneous deployment, cognitive radio, etc. In addition, a new direction has emerged, where Mobile Network Operators (MNOs) consider explicitly the energy sources and the associated economical and environmental costs [7].

[1] We use the terms *Cellular network* and *Mobile Network* interchangeably throughout this thesis.

Taking into account that Base Stations (BSs) are the major energy consumer in a mobile network, with 75 to 80 % of the total network consumption [8], powering them with Renewable Energy Sources (RESs) has the potential to become an indispensable tool for mobile network operators. Consequently, *Energy Sustainability* emerges as an essential concept, and poses a new question: How to use the harvested energy for sustaining the traffic demands, while meeting the quality of service requirements of end users? In fact, both energy efficiency and green-energy sources are promoted to be part of future mobile technologies. More specifically, the 5G era will witness increase in the importance of operational cost reduction, green-powered deployments and more sustainable and energy efficient networks [9]. In this regard, several projects have been developed such as Optimizing Power Efficiency in Mobile Radio Networks (OPERA-NET 1 and 2) [10], Energy Aware Radio and Network Technologies (EARTH) [11], Towards Real Energy-efficient Network Design (TREND) [12] and GreenTouch [13]. Our work is developed under Celtic Opera Net 2 European Project, which includes partners such as Orange, Thomson Broadcast, Nokia, Alcatel-Lucent, etc.

A promising direction in dealing with the energy demand increase of mobile networks is powering their BSs with RESs. One of the instinctive and popular justifications regarding Renewable Energy (RE) in general is the desire to render our society more environmentally friendly, e.g. by decreasing the global Greenhouse Gas (GHG) emissions. However, in addition to decreasing the GHG emissions, RESs can serve as a solution to many more problems. For example, using RE is proposed as a solution in areas where there is no power grid such as islands and deserts [1]. It also solves the problem for places where it is difficult or impossible to get connectivity to the power grid. Until now, mobile operators rely on diesel generators to run such BSs for most of these cases, which is not only expensive due to its price and transportation [14], but also one of the most polluting sources of energy. A program called *Green Power for Mobile* has been launched by the GSM Association to aid the mobile telecommunications industry to deploy various RE sources for powering 640000 new and existing off-grid BSs [15]. This action alone would save about 0.35% of the global diesel consumption. In addition, RE may also be part of the solution in case of a failure in the power grid [16] and the consequence of this failure on the communication itself, where 65% of communication interruptions are caused by power supply failures, and 85% of them are discovered after more than 12 hours, mainly due to users complaints [17]. Using RESs in this case has commercial sense for MNOs to support sustainable and profitable business.

In [18], the authors investigate the possible role of RE in reducing the deployment and running costs of the next generation cellular networks. Their study shows that it is economically suitable and environmental friendly to use RE sources in powering micro- and small- cell BSs, and that these resources can serve as basis for new business models. An example of these models would be the introduction of new spectrum regulations for licensing mobile operators capable of maintaining low maximum grid power consumption or maximum release of carbon emissions. Finally, the RE power can be seen as a source of revenue by the operators, e.g. by selling the excess energy to the grid, a use case particularly well fitted for developed countries with mature energy markets. Moreover, the developments in renewable technology are improving the efficiency of generating electricity, and resulting in decreasing the cost of deploying a green power system. For example, in the last couple of years the energy efficiency of solar cells increased to more than 41 %, which is more than twice the efficiency of the currently deployed ones [19].

Using RE to power cellular BSs makes not only environmental, but also economic sense, while at the same time opening opportunities for new business models. It is thus of great importance to study the subject in order to determine the potential gains, applicability scenarios, deployment strategies and new system architectures.

In the energy sector, significant efforts are put in the evolution of the power grid into a smarter one, the Smart Grid [20]. The ultimate vision is to have an all-encompassing power grid, which accommodates all electric appliances and allows bidirectional communication between them. The Smart Grid (SG) will be able to reduce the energy consumption and Carbon emissions and supply customers with more reliable services. Mobile networks can be considered as geographically distributed energy loads. With the advanced features of the SG, considering the SG is mandatory while studying the energy behaviour of on-grid mobile networks. In the following, we present the main objectives of this thesis.

1.2 Thesis objectives

Powering base stations with RE is a promising direction in the context of mobile networks. However, it is not trivial to design or operate such networks. In addition to Radio Resource Management (RRM), optimizing green mobile networks involves the optimization of the utilization of generated renewable energy. Moreover, considering a Smart Grid environment provides additional dimensions in the problem and introduces new research challenges. This thesis contributes to the domain of mobile networks powered by renewable energy sources and the power grid.

The work done here considers various trends found in the green networking literature to have a panoramic view of the existing studies and identify new cross-domain research opportunities. After an exhaustive study of the state of the art, we chose to consider the problem of minimizing the energy operational cost of mobile networks powered by renewable energy sources taking into account the Smart Grid environment. On one hand, the increase of the energy operational cost is one of the main concerns of mobile network operators. On the other hand, this will contribute in the decrease of the greenhouse gas emissions as every country has already included *Carbon emission taxes* explicitly or implicitly in the energy prices [21].

1.3 Project methodology

Our work was done under Celtic Opera Net 2 European Project [10]. The project addresses a wide range of topics concerning energy issues in mobile networks including material efficiency, hybrid energy sites, access network optimization and hardware design [22]. As a part of this project, we were mainly involved in optimizing the utilization of renewable energy and radio resource management. However, at each step of our work, exchanges with partners and discussions were done to evaluate the results and the feasibility of the proposed solutions.

We started by investigating the existing studies on green mobile networks. This permitted us to understand the proposed approaches in order to know the advantages and drawbacks of each technique and mechanism. More-specifically, our focus on mobile networks powered by renewable energy sources gave us the ability to determine the unresolved problems on this domain. In this regard, we were able to propose a new classification of research sectors, a model for Renewable Energy Base Station (REBS) and a framework for techniques and mechanisms. This allowed us to focus our research towards base stations powered by renewable energy in addition to the power grid.

Our next step was classifying the possible scenarios and objectives of using renewable energy in powering on-grid base stations. We designed new algorithms to minimize the energy operational cost of mobile network operators. To validate our approaches, we used computer simulations and real measurement provided by a European mobile operator. We used multiple real-world data sources, among which mobile operator measurement, renewable energy generation [23] and energy prices [24].

For each of our simulations, we considered a duration of 24 hours. The simulations are done for different distribution sets of users, levels of traffic, conditions of renewable energy generation and on-grid energy price variations. The simulated algorithms and mechanisms, including ours, are tested by taking their average results. In order to provide valid simulation scenarios we have consulted different standards and related documentation for mobile networks, more specifically for the Long Term Evolution (LTE) technologies, as well as establishing and reusing any common parameter, model or methodology provided by the partners, literature and collaborative projects deliverables in the energy-related field.

1.4 Novelty of our proposals

The study of the state of the art allowed us to have a wide overview of the existing work in the context of mobile networks powered by renewable energy sources [25]. As a result of this study, we designed a new framework that integrates approaches and mechanisms of green radio, with the specificity of using renewable energy sources, an important contribution to the state of the art.

In addition, we classify the possible scenarios and propose objectives of using renewable energy in powering on-grid base stations. In contrast to most of the existing studies that aim at utilizing renewable energy for reducing on-grid energy consumption, our proposals widen the options of using renewable energy in powering mobile networks [26]. Focusing on the objective of minimizing the energy operational cost, we propose several algorithms where base stations may work alone or as part of a network (with and without cooperation between base stations). In addition, we have investigated the effect of adding small cells powered by renewable energy on the energy operational cost of mobile networks.

Furthermore, we analyze and study the coverage, capacity and performance of a real deployed network of a European operator, and we propose two algorithms that aim at reducing the energy consumption and energy operational cost respectively. We also define a new concept: *Advance sizing* of renewable energy elements (renewable sources and energy storage). *Advance sizing* of renewable sources corresponds to dimensioning the size of renewable energy sources and the energy storage based on the operation of the network and variation of Smart Grid parameters, such as on-grid energy price.

Last but not least, we propose a new integration architecture for mobile networks and the Smart Grid. As an application to this architecture, we study a new behavior of renewable energy-powered base stations for which they provides ancillary services to the Smart Grid.

1.5 Thesis outline

The remainder of the thesis is organized as follows. Chapter 2 presents a survey of the state of the art on renewable energy powered cellular networks. Then, we classify the existing studies into research sectors and integrate the utilized mechanisms and approaches into a new framework. Chapter 3 introduces our methodology for determining the case study of on-grid base stations powered by renewable energy sources. It also describes the main tariff programs, and presents our algorithm for operating on-grid base stations powered by renewable energy considering real time on-grid energy pricing.

Chapter 4 extends the previous study considering the case of a network of base stations. After formulating the problem, we propose a new algorithm that allocates renewable energy, switches-off base stations, adjusts the transmitted power and determines the number of active resource blocks to minimize the energy operational cost of the network. Moreover, the effect of adding small cells solely powered by renewable energy is tackled in this chapter. In Chapter 5, we analyze the coverage and capacity of a real deployed network layout, and study the effect of renewable energy allocation and base station switching-off on the network energy consumption and energy operational cost.

In Chapter 6, we propose a new architecture for integrating mobile networks and the Smart Grid. We also study a new energy behavior of base stations powered by renewable energy and the Smart Grid, where base stations provide the grid with ancillary services. Finally, we conclude this thesis and present several potential research directions to be developed in future work in Chapter 7.

CHAPTER 2 Cellular networks powered by renewable energy sources

2.1 Introduction

This chapter is dedicated to the wide spectrum of studies on RE powered cellular networks. In [25], we presented a synthesis of the existing work, utilized tools and performance metrics used in this domain. This chapter is an extension of the paper and considers multiple additional references. We include a new classification of the existing work and propose a new framework that integrates the energy efficiency techniques and renewable energy system into two stacks of layers, where the interaction between layers and the impact of adding RE on the energy efficient techniques is presented.

The interest in energy efficiency in cellular networks quickly grew worldwide. In this sense, several overviews and survey papers have been written describing this topic such as [6],[27], [14],[28], [29], etc. However, all previous surveys were focused on the energy efficiency of wireless networks. The specificity of renewable energy powered cellular networks were not detailed, if mentioned at all. To the best of our knowledge, we were the first to survey the recent work in this field in [25]. Currently, there exist few surveys and reviews that consider powering wireless networks with RE such as [30] and [31]. Both reviews covers wireless communications powered by RE. However, this subject is too broad and the state of the art of cellular networks powered by RE was briefly described.

This chapter surveys the state of the art considering cellular networks powered by RES. We start by presenting a general view of the topic. Then, we present the existing work related to RE cellular system architectures, deployment experiments and dedicated algorithms in RE powered cellular networks. Based on these studies, we propose a new model for renewable energy base stations and detail its components. Moreover, we classify the previous work into research sectors and extend the framework presented in [6]. The preliminary work on cellular networks in a Smart Grid environment is then presented. Finally, we synthesize the performance metrics used in evaluating such networks before concluding.

2.2 Renewable energy in wireless networks

Wireless networks powered by RE are studied at two scales, small scale systems and large scale networks. Studies at the small scale focus on algorithms and protocols for point-to-point links powered by RE. The main objective is to maximize the throughput of the system considering various conditions and constraints such as existence or non-existence of storage, limited and unlimited storage capacity and variation and intemittency of RE generation [30]. Moreover, systems are studied for basic single-user channel or multi-user settings. Studies also consider cognitive radio networks powered by RE, where the aim is also to determine the optimal spectrum sensing policy to maximize the total throughput of the system under energy constraints [32]. For more information of recent advance on the small scale wireless network powered by RE see the exhaustive review of Ulukus et al. in [30].

In large scale, it is interesting to study the effect of introducing RE on the design and operation of wireless networks. Some examples of such networks are mobile ad hoc [33], wireless mesh [34] and cellular [25] networks.

2.3 Green mobile networks and renewable energy

Recently, studies are taking explicitly into account the availability and the specificities of RESs in the functioning of the cellular network infrastructure. Although a great number of renewable BSs have already been deployed in different places such as Japan, China, Austria, Africa, South Asia, South America, Latin America, Caribbean [27, 15] this domain is widely open to research and enhancement.

In [6], the authors classify different approaches on enhancing the energy efficiency of mobile networks into: component-level, cognitive radio, radio resource management, heterogeneous deployment and cell layout adaptation approaches. At the level of components, the work focuses on the power amplifier. Cognitive radio describes the process of sensing the radio spectrum and then reconfiguring the transmission parameters to adapt and match the channel conditions. Radio resource management is used to optimize the radio resources, such as bandwidth, for reducing the energy consumption. Deploying heterogeneous networks is beneficial not only for coverage and capacity extension but also for energy efficiency of cellular networks. Cell layout adaptation includes several techniques such as cell breathing and switching-off BSs.

Powering cellular networks with RE introduces a new concept, energy sustainability [34]. In comparison with energy efficiency that aims at reducing the total energy consumption, energy sustainability aims at utilizing the RE to sustain the users demands. Energy sustainability inherited some of the energy efficiency approaches. However, there is a need for new or update versions that suit the specificities of RESs in the functioning of the network infrastructure.

2.3.1 System architectures and cellular planning

Adopting RE in cellular systems affects the planning methodology and architecture of cellular networks. In [35], the author proposes several types of RE wireless structure and protocols for different network types, including cellular networks. Off-grid wireless networks powered by RE sources and batteries may suffer from energy unavailability for some time causing the interruption of the services. The Coverage Supply Redundancy Architecture (CSRA) is introduced as a solution. For RE sources, the author proposes using different kinds of generators (solar, wind, etc.) to reduce the possibility of BSs outage and explain why it is not trivial for neighboring BSs to connect to each other through a power line, e.g. for financial reasons. However, it is technically feasible and economic for neighboring BSs to support each other wirelessly. BSs are placed in smaller inter-cell distance (less than the usual planning) and transmission power is varied based on RE availability. To further stabilize the power supply, some CSRA BSs can be augmented with other energy sources such as fuel based or power grid.

An advanced architecture based on the 3rd Generation Partnership Project (3GPP) Heterogeneous Network (HetNet) is presented in [18], as illustrated in Figure 2.1. It defines a multi-tier, self-organized wireless access network composed of several types of BSs with different characteristics using the same access technology and spectrum. The architecture consists of a grid-powered macro BSs and overlapped micro- and small-cells powered by RE or grid depending on their conditions (location for example). This architecture keeps the benefits of the fully grid powered HetNets such as long time cost saving, and provides easier deployment for BSs difficult to be connected to the power grid and reduction of carbon emissions. A similar architecture is adopted by [36] where the authors considered the system model as a high power BS powered by grid

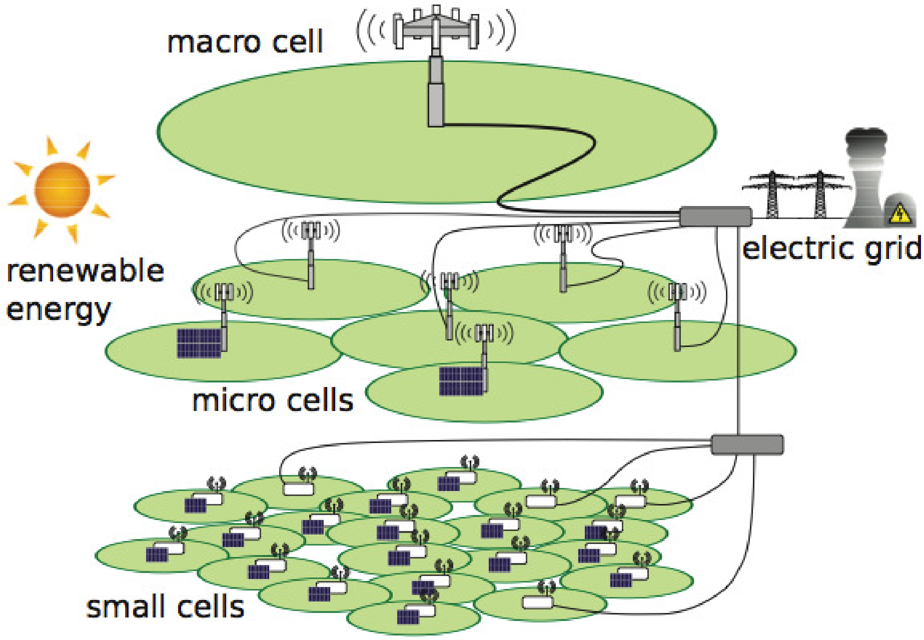

Figure 2.1: Renewable HetNet architecture [18].

overlapped by several low power BSs powered by RESs only. As these architectures are quite general and depend on the state of deployment, it would be of great importance to perform more detailed analysis of their real-world applicability.

In [37], planning of cellular networks equipped with RESs is investigated. The study takes into account satisfying the users and reducing the Capital Expenditure (CapEx) and Operational Expenditure (OpEx). The problem is to select the subset of candidate BSs with minimum cost (sum of CapEx and OpEx), where BSs are connected by dedicated power line connections for energy balancing from other RESs, a concept introduced in [38]. The problem is shown to be NP-hard, and thus heuristic algorithms are used for cellular planning. The solution consists of two phases, Quality of Service (QoS)-aware BS deployment and energy balancing connection. In the first phase, the authors assume that there is no power connection between RE sources, and solve the problem based on the QoS constraints. The second phase starts with a fully connected topology (BSs are connected with power lines), and then removes connections with minimum amount of transferred energy until no cost saving is achieved.

2.3.2 Deployment experiment and renewable energy system dimensioning

In 1995, AT&T proposed to use renewable energy sources to power their products, such as Photovoltaic (PV) systems for wireless micro cells [39]. In [40], an integrated solution to dynamically decrease the power consumption of wireless BSs and power them with RE is presented. The authors propose several migration steps towards large deployment of alternative energies in off-grid or poor grid sites. The primary migration step consists of replacing one diesel generator with a deep-cycle battery bank to provide energy when the generators are switched off. The next step consists of deploying a single alternative energy source to reduce the diesel generators' run time and consumption. The ultimate migration step is to deploy a mixture of alternative energy sources. One pre-existing diesel generator may remain to address the worst-case climatic conditions. This prototype has been tested in Alcatel-Lucent Energy Lab facilities near Paris.

Due to the characteristics of RESs and variation of traffic, and thus the energy demand, precise sizing of RESs and energy storage is essential to avoid any system failure and/or additional cost. Thus, many studies investigated the feasibility of using RESs and studied equipment sizing of cellular BSs powered by RE. In [41], the authors propose a new configuration of a standalone PV/wind hybrid energy system with a backup diesel generator for cellular BS sites in isolated areas of central India. The methodology used in this feasibility study is based on power produced by wind/solar sources and data load. The results provide indications as to what should be the requirements to the wind turbines, the solar panels, the battery bank and the backup diesel generator. Finally, the environmental, technical and economical impacts are studied for Bhopal in central India. In [42], the authors consider the problem of dimensioning RESs for powering LTE BS. The used methodology is as follows: 1) the energy need of the BS is evaluated based on BS energy consumption model and traffic profiles, 2) photovoltaic panels are diminished based on the daily energy need of the BS and typical radiative power of sun in specific locations 3) energy storage is evaluated to satisfy the needed capacity to absorb energy production variability due to both daily and seasonal radiative power variations 4) Finally, the effectiveness of integrating the PV system with wind turbines is studied.

As a powerful tool for designing both on- and off-grid energy systems, HOMER can be used in sizing and dimensioning renewable sources and storage [43]. It can provide a good evaluation of the economic and technical feasibility of a large number of technology options and to account for variations in technology costs and energy resource availability. As an example, the authors of [44] present a feasibility study and analyze the optimal size of a stand-alone hybrid solar/wind powered system of BS in Nepal. The authors used HOMER and mathematical models implemented in MATLAB for performing the feasibility analysis and calculating the optimal configuration for a given load and desired probability of power outage. The model is provided for multiple combinations of PV arrays, wind turbines, batteries, temperatures, reliabilities and system costs. Then based on these parameters, an iterative approach is adopted where all of the combinations are tried and the best one is chosen. Also, the authors of [16] used HOMER to study the feasibility of implementing RE for an on-grid BS as a solution for power failure and high fuel cost in Bangladesh. The proposed system is composed of PV cells, a battery, a converter, a diesel generator and connection to the power grid. The study showed that the proposed system is more environment-friendly and cost-effective compared to traditional BS, although it requires significant initial investments.

Another approach is proposed by [18], where the authors considered sizing the renewable energy (PV arrays) and storage system of next generation cellular networks envisions adopting the heterogeneous architecture described in [14]. The approach calculates PV land occupation and the storage size. The PV land occupation is calculated based on the BS power needs and number of hours of available solar insolation. To size the energy storage system, the amount of energy accumulated through a day is calculated. Then, for macro cells, the storage device nominal power is calculated for two extreme sky conditions, i.e. seven contiguous days of clear sky and seven contiguous days of heavily clouded sky. These two conditions are used to calculate the maximum capacity of the energy storage. For micro- and small-cells, the capacity of the storage for a site is calculated based on the average between the two extreme condition nominal powers. The authors assumed that the availability of micro and small cells is not mandatory, thus the storage system rating can be reduced.

In [45], the problem of sizing the RESs and the energy storage for a base station is tackled. The RE arrival, storage state and energy consumption are modelled as a discrete markov chain. The objective is to design a reliable and economical RE powered BS, which guarantees communication reliability, system durability as well as minimum capital expenditure. The problem appears to be NP-hard and a genetic algorithm is used to find the solution.

2.3.3 Dedicated renewable energy algorithms

After powering mobile BSs with RE, the fundamental design criteria of performance metric has shifted from energy efficiency to energy sustainability [46], i.e. whether the harvested energy can sustain the traffic demands and meet QoS requirements of end users in the networks. Applying this concept is essential in any mobile system equipped with RES. In this context, the harvested energy must be utilized in an efficient way. Still, the two concepts energy efficiency and energy sustainability are consistent with each others as it is easier to to power a mobile network with RESs if it consume less energy. In the following we present studies that consider RE in powering cellular networks to highlight on the approaches are used for increasing the utilization of RE.

In [47], the authors propose an intelligent energy management service for green BS. The method predicts the RE generation and energy consumption based on both the weather forecast and the site's power consumption historical data. A heuristic algorithm, based on the stored energy, is used to adapt the transmitted power output of the BS to maximize the utilization of RE and avoid service outage. At the level of network, the problem of energy outage of BSs purely powered by RE, in a cellular networks with BSs powered by either RE or the power grid is studied in [48]. The challenge lies in the possible energy outage of BSs powered by RE, and this will lead to network coverage hole and thus severely affecting the service quality. Sleep mode policy is used to reduce on-grid energy and allow renewable BSs to store RE for future use when the traffic does not match with the energy arrival. Dynamic programming is used to achieve the optimal solution and a simple heuristic algorithm is proposed. Compared to a greedy scheme that utilizes RE whenever possible, the proposed algorithm achieves lower outage and more users are served.

Moving to heterogeneous networks, the problem of maximizing the number of accepted users in a 2-tier Hetnet solely powered by RE and equipped with energy storages is tackled in [49]. BSs across tiers differ in terms of energy harvesting rate, maximum transmit power and deployment density. To address this problem, adaptive user association based on RE availability is proposed. An offline algorithm and a heuristic on-line algorithm inspired by gradient descent based user association is proposed. In [50] and [51], the authors study the availability of BSs in a k-tier Hetnets. Bases stations are powered by RE only and each tier has its own RE arrival rate, storage capacity, transmit power and density. The BS is considered available when it have enough RE to serve at least one user. In case of unavailable BS, the users are served by neighboring BSs, which allow it to recharge the storage. Using tools from from random walk theory and stochastic geometry, the authors characterize the fraction of time each type of BS can be kept ON where each BS toggles its ON/OFF state independently of the others. The authors proved that there is a fundamental limit on the availabilities of BS, which cannot be surpassed by any uncoordinated strategy. As a part of the proof, they construct the strategy that achieves this limit. In [52] the call completion problem of a two-tier heterogeneous network with energy harvesting BSs is tackled. The location of macro BSs, micro BSs and users are modelled as independent Poisson Point Processes with constant densities. The upper and lower bounds of the call completion probability is calculated, and the impact of the system parameters such as storage capacity, the minimum energy level at which BS switches back ON and energy harvesting rate are examined. Results show that macro BSs energy harvesting parameters have the dominant impact on the call completion probability.

Renewable energy-based clustering is considered in [53] to improve the throughput of a network of base stations powered by only RESs. Each BS uses the harvested energy for transmission and becomes inactive when the harvested energy is less than the required energy for transmission. The authors derive the outage probability and the area spectral efficiency for an energy-harvesting clustered wireless network in closed form using stochastic geometry. Then a spectrum-efficient operating policy based on the energy state parameters for energy-harvesting BSs is proposed, where each BS serves only the closet n users instead of serving all the users in the cluster. Results show that the spectral efficiency is increased by the proposed policy.

The previous studies focus on BSs that are solely powered by RESs. Other studies consider BSs powered by both renewable and non renewable energy sources. For example, the trade-off between user average satisfaction degree and the ratio of RE used in powering a mobile BS is introduced in [54]. The authors consider real traffic profile and statistical energy generation deprived from real weather. The trade-off is then studied for different configuration of a mobile BS. In [55], resource allocation problem of a single BS powered by RE and the grid is studied. The problem is formulated as a minimization of the average grid power while satisfying the users quality of service (outage probability). For a given time the power-outage trade-off is calculated using statistical information of traffic intensity and harvested RE. Dynamic programming (DP) and some heuristics are used to solve the problem, where results shows that DP algorithm outperforms the heuristics in terms of grid power savings. In [5] the authors proposed two detailed approaches, the handover parameter tuning for target cell selection and power control for coverage optimization. In other words, the mobile users are guided to associate with BSs powered by RE, which will reduce the on-grid energy consumption. They showed that these two approaches can result in a balance between the energy saving and the throughput impact.

Optimizing the cell size for energy saving in cellular networks powered by both RE and the grid is studied in [56]. The authors state that maximizing the utilization of harvested energy involves at least two aspects. The first aspect is the multi-stage energy allocation problem that determines how much energy should be used at the current stage and how much must be reserved for future. The second aspect is maximizing the utilization of allocated energy in every stage. Consequently, the problem of cell size optimization is decomposed into two sub-problems: Multi-stage Energy Allocation (MEA) and Minimizing Energy Consumption (MEC). A simple algorithm for energy allocation is proposed to allocate the amount of RE used by each BS at each stage based on their demand and the condition of their storage. For the second sub-problem, the authors propose two steps algorithm: 1) minimizing the on-grid energy BSs, 2) maximize the number of BSs that can be switched into sleep mode. Finally, the authors combine the MEA algorithm and the MEC algorithm to solve the cell size optimization. The authors of [36] propose Intelligent Cell Breathing (ICE) algorithm to optimize the utilization of green energy in cellular networks by minimizing the maximal energy depleting rate of BSs powered by RE sources. The authors considered heterogeneous networks with a mixture of a high-power BS powered by grid and low-power BSs powered by RESs. The formulated problem aims at minimizing the maximum power depletion rates of the low-power BSs. An algorithm called ICE is proposed as a solution for the min-max problem to achieve low computation complexity. The algorithm shrinks the coverage of low-power BSs by reducing their beacon power levels. The overall energy consumption can be increased but the amount of grid energy consumption is reduced.

An optimal user association algorithm for delay and power consumption tradeoffs in HetNets with hybrid energy sources is studied in [57]. The BSs are powered by a combination of power grid and RE. The problem is formulated as a convex optimization that aims at minimizing the weighted sum of the cost of the average traffic delay and the cost of on-grid power consumption. A user association algorithm is proposed to enhance the QoS by minimizing the average traffic delay, as well as reducing on- grid power consumption. Similarly, the problem of user association in heterogeneous networks powered by RE and the power grid to reduce the grid power and enhance the QoS is studied in [58]. The authors consider a mixture of macro- and pico- BSs each equipped with solar panels without an energy storage, and the problem is formulated as joint optimization of grid energy and traffic delivery latency. A distributed user-association scheme is proposed where the BS measures the traffic load and harvested energy and advertise the BS energy-latency coefficient. The user selects the corresponding BS based on this coefficient. Results shows that the proposed algorithm reduces the on-grid power consumption and avoids congesting the BSs at the same time.

In [59], Coordinated Multipoint (CoMP) transmission to enhance the utilization of RE in a renewable energy cluster formation is employed. Considering that each BS is powered by both RE and the power grid and equipped with large energy storage, the authors propose a renewable energy aware cluster formation that aims at minimizing the grid energy consumption. Due to the complexity of the problem, a two stage algorithm is proposed. First, the cluster is formed to serve as much as possible of users by exploiting renewable energy. In the second stage, cluster formation is performed for users that remain non served after the first stage. Results show significant grid energy consumption reduction.

The concept of energy sharing between BSs powered by renewable energy and the grid is proposed in [38]. Each BS is powered by conventional energy sources (power grid) and equipped by RE sources and finite capacity energy storage. BSs are connected by resistive power line for energy sharing. The authors find the optimal energy cooperation using linear programming in the case where energy and demand profiles are considered deterministic. On the other hand, on-line greedy algorithm is proposed for the case where energy and demand profiles are stochastic. Moreover, the authors study the effect of availability of energy state information on the gain of the energy cooperation in terms of reducing conventional energy consumption.

2.4 Renewable energy base station model and classification framework

2.4.1 Renewable energy base station model

In [25], we proposed the Renewable Energy Base Station model, see Figure 2.2. This model is a basis for understanding the impact of using RE in powering mobile base stations and is constructed as a synthesis of many studies. We concluded that multiple factors should be modelled in order to correctly analyze a BS powered by RES. Some of the major parameters and elements include the type of the BS, energy sources (and their models), power control policy and traffic model of the users. The user traffic model is a classical problem in cellular networks with vast amount of dedicated studies and will not be discussed in this thesis.

In our context, a REBS uses at least one type of non-fuel renewable energy sources such as PV systems or wind turbines (e.g. bio-fuels are excluded, except when specifically mentioned). Figure 2.2 presents our REBS reference model, which we are using as basis in this thesis.

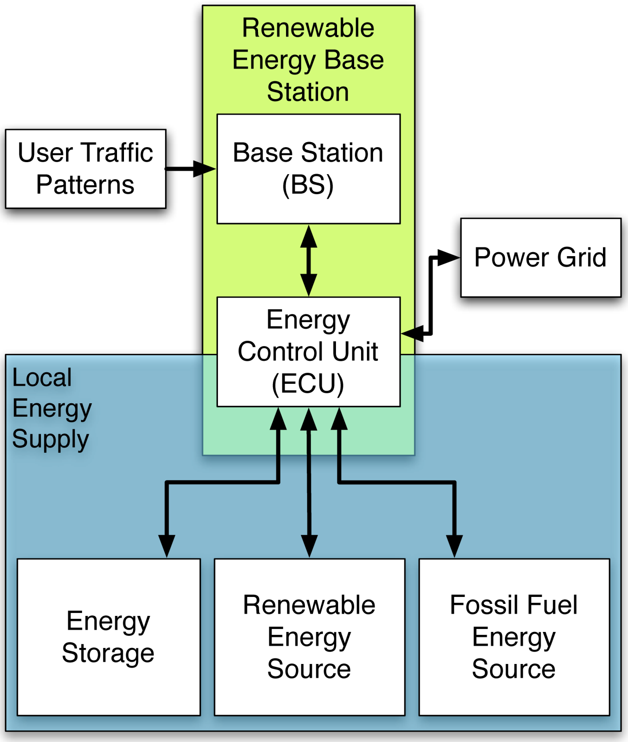

Figure 2.2: Renewable energy base station (REBS) model.

Types of Base stations

Several types of BSs are found in the literature such as those supporting micro, femto pico and macro cells. Each type has its specific coverage capability, energy consumption, deployment order and cost [60, 18]. Macro cells are distinguished for their high coverage and can support large number of users. However, this type of BS has high energy consumption profile, which is in order of thousand of watts. Macro BSs are deployed by the operator and have very high CapEx and OpEx. Micro cells are known for their shorter range, lower energy consumption profile and lower CapEx and OpEx with respect to their macro counterparts. Operators are capable of deploying them rapidly and for relatively low cost. Small cells (pico- and femto- for example) are characterized by low range and low power. They are typically used to extend coverage and improve capacity. Such kind of BS can be deployed on a limited space and can be installed temporary for special events.

Power model

The power consumption of a conventional BS site depends on traffic load. Considerable variations in average traffic could be observed with radio network over a 24 hour period.

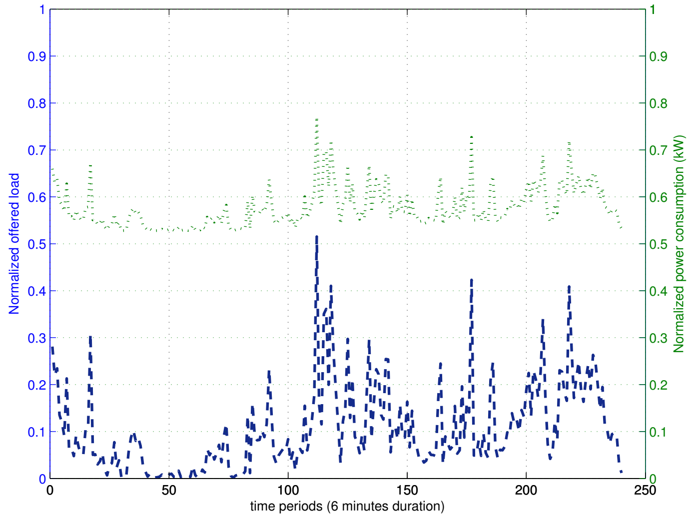

Figure 2.3: Normalized power consumption (with respect to power at full load) and offered traffic for a real macro BS site.

Irrespective of huge variation in traffic volume, energy consumption does not follow the similar variations. This fact could be observed in Figure 2.3, which corresponds to the normalized power consumption and normalized offered load of typical macro BS site consisting of 3 sectors operating with 10 MHz bandwidth. Thus it is important to define a power model to correctly analyze the energy behavior of base stations.

Several models of the energy consumption of cellular BSs can be find in the literature such in [61]. One of the most detailed was developed as a part of the Energy Aware Radio and Network Technologies (EARTH) project [60]. The proposed model can be used for different type of BSs (micro, macro, pico and femto) and takes into account multiple factors. It is summarized by the following equation:

$$P_{in} = N_{Trx} \cdot \frac{\frac{P_{out}}{\eta_{Pa} \cdot (1-\theta_{feed})} + P_{RF} + P_{BB}}{(1-\theta_{DC})(1-\theta_{Ms})(1-\theta_{cool})} \tag{2.1}$$

where P_{in} is the input power, N_{Trx} is the number of transceivers, P_{out} is the transmitted power, η_{Pa} is the efficiency of power amplifier, P_{RF} is the power consumed by the radio frequency chain and P_{BB} is the power consumed by baseband engine. θ_{DC},θ_{Ms} and θ_{cool} represent the losses incurred due to DC-DC power supply, mains supplies and active cooling respectively. The feeder loss of a macro BS may be mitigated by introducing remote radio head, where the power amplifier is mounted at the same physical location as the transmition antenna. The relation between RF output power and BS power consumption is nearly linear as shown by [60]. Hence a linear approximation of the BS power model is justified as follows:

Table 2.1: Power model parameters of different BS types [60].

BS type	N_{Trx}	P_{max} (W)	P_0 (W)	Δ_P	P_{sleep} (W)
Macro	6	20	130	4.7	75
RRH	6	20	84	2.8	56
Micro	2	6.3	56	2.6	39
Pico	2	0.13	6.8	4.0	4.3
Femto	2	0.05	4.8	8.0	2.9

$$P_{in} = \begin{cases} N_{Trx}.\left(P_0 + \Delta_p * P_{out}\right), & 0 < P_{out} \leq P_{max}, \\ N_{Trx}.P_{sleep} & P_{out} = 0. \end{cases} \tag{2.2}$$

where P_0 is the power consumption at the minimum non-zero transmitted power, Δ_p is the slope of load-dependent power consumption and P_{sleep} represents the power consumption in sleep mode. The table of power model parameters of different BS types [60] are presented in Table 2.1.

Energy sources

In general, energy sources are classified into 3 types: fossil fuel, nuclear and renewable [62]. This classification is related to the type of resources from which energy is generated from. In this document, energy sources corresponds to the energy supply of the BSs, which are the power grid, on-site Diesel generator and on-site RESs. The main characteristics of the power grid and RESs are described in the following.

Power grid and Diesel generators When studying a BS powered (partially or completely) by the power grid, it is assumed the power grid is an unlimited source of energy. This assumption is valid and used in most of the studies. On one hand, the traditional energy customer is not responsible of the stability of the power grid. On the other hand, the power grid is managed to meet the energy demands of the users. In some cases where the power grid suffers from failures, the grid can be modelled by ON-OFF model or other models that represent the frequency and duration of failures [63].

Despite the fact that the energy efficiency of the diesel generators decrease with time due to usage, their energy generation is deterministic. Consequently, dealing with them is also straight-forward.

Renewable energy sources Renewable energy sources do not generate stable quantities of energy and are influenced by multiple parameters [27]. For example, the performance of solar panels is determined by the quantity of sunlight, snow fall, cloud coverage, smog, air density, temperature and others. Similarly, wind energy production is affected by many elements such as wind power, altitude, obstructions, air temperature, etc. One of the major approaches to compensate the intermittence of these energy sources is the usage of energy storage.

Energy storage There are several ways to ensure the reliability of RE systems [64]. Systems may combine more than one type of RE source to have a better chance of being able to supply the load more consistently because they might have different times of low and high generation. However, in some cases this is not sufficient. Energy storages are introduced in order to maintain the energy balance within the RESs. They enable energy to be stored when there is an excess of supply, and provides the missing energy to the loads to compensate for the deficit of supply. Many types of storage are found depending on the scale they are used for. The most frequently used type is batteries. Batteries form a large part of the CapEx of RE systems and it is important to manage the system to ensure them maximum lifespan. This is achieved by controlling its charging and discharging cycles. In addition, the system must be dimensioned correctly to ensure that the power demand is always met by the supply and to minimize the total cost of the system [18].

When studying the performance of base stations equipped with energy storages, it is essential to consider some characteristics [64, 45]. The efficiency of the storage determines the amount of energy lost during the storing process. The capacity of the storage corresponds to the maximum amount of energy that can be stored. The self discharge rate, loss of stored energy, and degradation of the storage, e.g. decrease of capacity, should be considered when studying the system at large time scale. Finally, respecting the maximum charging and discharging rate ensures the normal functioning of storages.

Renewable energy models Dealing with renewable energy sources is not easy, due to their inherent intermittence and variance in the performance. Thus, a suitable RE generation model is essential in designing, studying and evaluating the performance of RE powered systems. Several approaches are used in studying such systems which include deterministic [65, 66], statistical [54] and stochastic [67] models.

In deterministic models, RE generation is known in advance. It is justified by the possible prediction of the energy generation of some renewable sources. This model is used in small time periods when RE can be considered constant [66]. However, the model is no longer practical when the studied time period is increased. In practice, deterministic model can be used as a reference case to study the optimal energy allocation strategies and design suboptimal algorithms as in [68].

Statistical models are based on real RE generation profiles provided by real measurements, such as in [44] or renewable energy calculators, such as in [16, 42]. These models provide the periodic (e.g. each hour) amount of generated energy for a given system configuration and are used in simulating algorithms and designing RE systems.

Due to the intermittence and fluctuation of renewable energy generation, the harvesting process is regarded as a random process. Although some studies may consider using the ON-OFF model [69], this model is not suitable for cellular networks since the amount of harvested RE (and not only the availability) is important. Solar energy arrivals is modelled as a Poisson process in [70]. In [67] the energy harvesting process is modeled as a Discrete-Time Markov Chain with a maximum number of harvested states H. The harvested and stored energy is assumed to be in integer units with a granularity proportional to the total harvested energy. Based on this assumption and that the consumption of a BS follows a random process, the energy flow behavior of RE powered BS is modeled as a M/G/1/K queuing system, where the capacity of the energy storage bank is represented to be K energy units. In [46] the authors modelled the state of energy storage as G/G/1 queue with arbitrary random processes of energy arrival and departure, characterized by a mean and variance. The values of the means and variances can be estimated by exponentially weighted moving average or other approaches. Diffusion approximation is applied to analyze the energy buffer and depletion probability of a node.

Energy control unit

Due to the unreliability of RE sources, an energy control unit (ECU) (or alternatively power control unit) is essential for managing the changes in energy generation and consumption [47]. In case the RE cannot satisfy the energy demand of the BS, the control unit will compensate the needed energy from the back-up storage or the power grid if such connection exists. In the case of excess RE, the control unit will use it to recharge the batteries. Additionally, we envision that the ECU would operate in a more advance way by taking the decision of storing, consuming, buying and selling energy.

2.4.2 Off-grid and on-grid base stations

The work presented in Section 2.3 can be decomposed into two main axes. The first axis considers self-powered networks, where BSs are powered by local renewable energy sources (solar panels, wind turbines) and possible fossil fuel generators. These BSs are called stand-alone or off-grid BSs. BSs are not able to share renewable energy between each other, and the possible cooperation is to support each other wirelessly by adjusting the transmitted power and/ or offloading users. Under this scenario, the main objective of any architecture deployment or algorithm is to maximize the utilization of renewable energy to sustain the service of users in the network. The REBS model presented in the previous section can be applied considering that the grid does not provide energy to the BS.

The second axis considers networks powered by local energy sources and the power grid. BSs in such networks are called hybrid-energy or on-grid BSs. One of the frequent usage of renewable energy in this case is to minimize the on-grid power consumption. Nevertheless, this might not represent the real utilization of renewable energy and can be extended into more objectives (see Section 3.2.2).

2.4.3 Research classification

In this section, we classify the studies and proposals presented in Section 2.3. Table 2.2 presents our general classification for these studies where each research sector uses specific tools to achieve it main objective. Moreover, we highlight the main challenges of each of the research sectors.

Following this classification, the tools and algorithms used in operating on-grid and off-grid BSs can be integrated in a framework model. This framework model is an extension of the one used for energy efficient techniques proposed in [6]. The framework for energy efficient techniques proposed in [6], which we will denote as energy efficient stack, and our updated framework are presented in Figure 2.4 and Figure 2.5 respectively. We introduced a new stack, which we call RE stack, representing the RE system and its interaction with some energy efficiency layers. In the following we present the layers of both stacks and the impact of the new framework.

In energy efficiency, the enhancement in the component layer allows to relax the design constraints and facilitate the operation of the upper layers. Hardware components of a BS are developed to reduce its energy consumption. Considering the component approach as the solution of all the problems is rather insufficient in order to achieve large-scale savings. A significant amount of energy is wasted due to underutilisation of

Research sector	Main idea	Tools and algorithms	Challenges
Network architecture and cellular planning	New or updated architectures and planning methodologies are essential for the functionality and effectiveness of using RE in powering cellular networks	• Using redundancy to allow BSs to support each other wirelessly [35] • Adopting heterogeneous networks [18] • Wired energy connection between BSs [37]	• New dimensions are added to the traditional planning schemes making the process more complicated • Availability of free space in the site location to deploy the RE systems • High capital cost due to infrastructure
Renewable energy and storage dimensioning	Determining the correct size of RESs and the storage is essential for the feasibility and cost of the energy system	• Software simulators such as HOMER [43] • Mathematical calculations [18] • Stochastic system design [45]	• Over- or under- sizing of energy systems • Non of the studies considers radio resource management or network operation when sizing the energy systems • The dimensioning process is location dependent
Operation of off-grid BSs (Self sustainability)	The BSs are solely powered by RE and the main objective in this case is self sustainability.	• Energy management • Energy efficient approaches • Energy sharing between BSs • Heterogeneous networks	• Coverage hole due to outage of RE powered BSs [48] • Blocking users far from the BS [53] • Availability of BSs is limited in case of uncoordinated strategy between them [50] • Service availability is highly affected by macro- base stations energy system, which usually needs high investment cost and free space to deploy RE system [52]. • Need further work specifically on traffic shaping techniques as the priority is continuity of service
Operation of on-grid BSs	BSs are powered by RE and the power grid. RE is frequently used for decreasing on-grid energy. However, we propose more objectives in Chapter 3	• Energy management • Energy efficient approaches • Energy sharing between BSs • Heterogeneous networks	• Need for a new definition of RE utilization due to the variation of the grid parameters • The evolution of the power grid into Smart Grid impose the necessity for cooperation between the Network operators and the Smart Grid • Mobile networks and the Smart Grid is a new domain that is needed to be studied for the benefits of both entities

Table 2.2: Discussion of renewable energy cellular networks research issues and challenges.

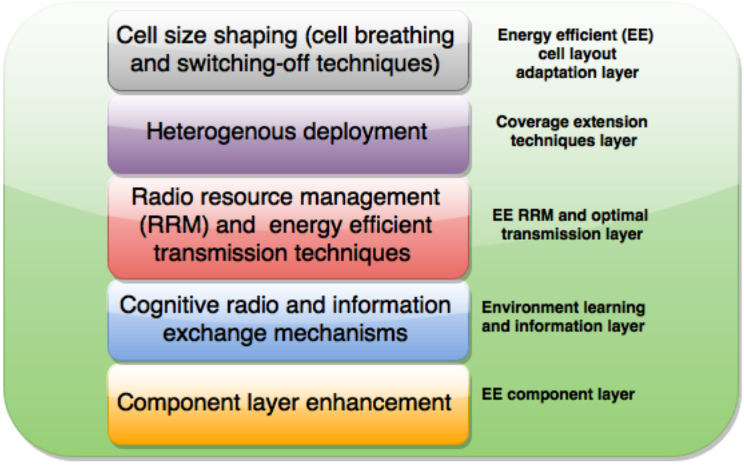

Figure 2.4: Framework of energy effecient approaches in cellular networks [6].

radio resources. That is the reason for having upper layers above the components. The next layer is the environment learning and information exchange layer, where the cognitive radio capabilities would adapt the radio devices transmission parameters based on sensing the channel conditions. Moreover, information about neighboring BSs are complementary and are utilized at the upper layers. This will lead to finding transmission strategies that optimise energy efficiency at the RRM level and allow switching-off BSs at the cell layout adaptation layer.

At the RRM, the efforts of the lower two layers allow the design of energy-efficient RRM and optimal transmission mechanisms. Trade-offs, such as spectrum-energy, bandwidth-power and delay-power should be analyzed to achieve a good balance among the spectrum, energy consumption and time delays. Moreover, knowing that the future of cellular network goes toward the heterogeneous architecture and BS cooperative transmissions, such as CoMP, there is a lot of work to do in coordination mechanisms of resource allocation and usage of multi-tier network for more efficient network. Finally, we have the cell layout adaptation layer. The main mechanisms at this level are switching-off and cell-breathing schemes that provide savings at a network scale. The coverage and capacity extension added by deploying heterogeneous network and the existence of high capacity and energy demand macro- BSs impose the need for efficient switching-off mechanisms to increase the efficiency of the network.

Now, we present the RE stack and explain the interaction of this stack with the energy efficient stack. We should note that introducing RE as the main source (off-grid) or one of the sources (hybrid) changes the objective of reducing the energy consumption. The mechanisms are now used for satisfying the demands or minimize the non renewable energy consumption. In the latter case, the total energy consumption may increase

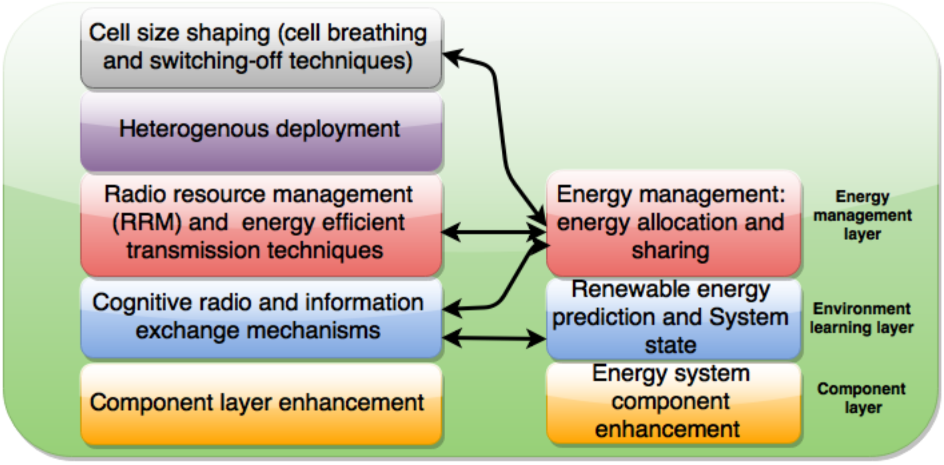

Figure 2.5: Our proposed framework of approaches in the context of cellular networks powered by renewable energy.

but the non-renewable energy consumption decreases. In the RE stack, enhancing the system component of the energy system permits more harvesting of RE and lower loss when storing it. Although, there is no direct interaction between component layers of energy efficient and RE stacks, they both lead to reducing the cost of the energy system in the dimensioning step (size of RES and the storage). On one hand, the energy demand of the BS is decreased in the energy efficient stack. On the other hand, the size of renewable sources needed for generating a given amount of energy and the energy loss due to storage efficiency are deceased in the RE stack.

The next layer of the RE stack is the environment learning layer, where the energy system would learn its characteristics (efficiency, peak energy generation,etc.), allow RE prediction and exchange the storage state and energy generation information with other BSs. This will allow better utilization of RE and help the decision of energy management at the Energy management layers. In fact, exchange of information between the environment learning layers of both stack is very important. On one hand, the upper layers of the energy efficient stack will have more information concerning the RE generation and storage state. This will lead to more efficient network where RRM, adjustment of the transmission power and switching-off mechanisms can be adapted to the conditions of the energy system. For example, a base station with high renewable energy availability increases its transmission power and share this information with a neighbouring base station, with low RE availability, allowing it to switch-off and recharge its energy storage. On the other hand, the energy system would know more about the energy demand of the network and have better decision at the energy management layer.

Finally, the decision of using, storing or selling RE is taken at the energy management layer. This layer is also responsible for the interaction with different layers of energy efficient stack. For example, the number of active resource blocks of a BS can be determined based on the amount of available RE. Grid energy can be purchased (in hybrid BSs) in case the BS requests more energy due to user traffic and unavailability of RE or the storage. In higher scale, the allocation of RE at each BS may affect the size of the cell, where BSs with high RE availability can increase their coverage to allow BSs with lower RE to shrink its coverage or switch-off. In general, the best approach combines RE allocation and energy efficient approaches and iteratively converge to the required objective (e.g. availability of service or minimizing the grid energy).

2.5 The Smart Grid and mobile networks

Considering RE for powering cellular networks attracted attention, and the problem of utilizing the generated RE as well as the radio resources in this context was investigated in several studies. Concurrently, another topic has seen rapid development, where significant efforts are put in the evolution of the power grid into a smarter one, the Smart Grid [20]. Thus, academia and industry started considering the Smart Grid when studying cellular network energy behavior. For example, the authors of [71] study the operation of cellular BS powered by Smart Grid considering traffic variation, real-time electricity price, several energy providers and the pollutant level associated with electricity generation. However, powering BSs with RESs is not considered. On one hand, CoMP is used to ensure acceptable service quality in the cells whose BSs have been shut down. On the other hand, the active BSs decide on which retailers to procure electricity from and how much electricity to procure. A Stackelberg game is formulated consisting of two levels: cellular network level and Smart Grid level. Simulation results show that the SG has significant impacts on green wireless cellular networks, and the proposed scheme can significantly reduce the operational expenditure and CO_2 emissions.

Another study done in [72] analyzes green cognitive mobile networks with small cells in the SG environment without considering RE. Power allocation and interference management for multimedia communications are performed to serve the demand side management service. The problem of electricity price decision, energy-efficient power allocation and interference management is formulated as a three-stage Stackelberg game, where a Bertrand game with asymmetric costs is used to model price decisions made by the electricity retailers. A backward induction method is used to analyze the proposed Stackelberg game. Simulation results show that the proposed scheme can significantly reduce the operational expenditure and Carbon emissions using cognitive radio and small cells for multimedia communication.

The two previous studies did not consider the use of RE in powering the BS. However, the authors of [73] study adaptive power management for wireless BS powered by local RESs and the Smart Grid under several uncertainties such as generated power from renewable sources, power price from the electrical grid, and power consumption of the wireless BS due to varied traffic. The aim is to minimize the cost of energy consumption as well as meet the users demand. A multi-period stochastic programming model is formulated and then translated into linear programming for finding the solution of adaptive power management. Results have shown that the optimal decision of adaptive power management can successfully minimize the power cost. Similarly, the study done in [74] considers the problem of minimizing the electricity bill for a cellular BS powered by the Smart Grid and locally harvested RE. The authors consider hourly-varying electricity prices known a day ahead by the BS. Several online energy management strategies that require only causal knowledge of RE generation and the power consumption profiles are proposed and compared with the optimal energy management policy. The latter assumes perfect knowledge of all system parameters. Simulation results show that the performance of the proposed online strategy deviates from the optimal by 2% at most. These studies focus on the energy management (RE allocation and storage management) and do not discuss any energy efficiency technique.

In [75], a new architecture for powering green mobile networks with a majority of renewable sources is introduced. The architecture consists of a cluster of BSs powered by local RESs and the power grid and equipped with energy storage. Renewable energy sources and the energy storage may be centralized or distributed. However, they are shared by all BSs using a microgrid configuration in both cases. The microgid configuration allows more tightly coupled management of resources with the electric power grid status. In order to increase the utilization of RE, one of the BS is switched-off even when the traffic load is not low. A traffic shaping technique that slightly reduces the quality of voice traffic is employed.

In [76], the authors consider a network of BSs powered by RE and several electricity retailers, where the aim is to minimize the energy consumption, reduce the CO_2 emissions and maximize the profit of the network operator while maintaining a certain QoS. The problem is solved by a heuristic algorithm that switches-off redundant BSs and procures power from retailers without affecting the QoS of the network.

The study in [77] considers the problem of minimizing the on-grid energy cost of a heterogeneous cellular network with BSs powered by RE and the Smart Grid considering real time pricing. A two stage optimization problem is formulated where transmitting powers of BSs are adjusted while QoS experienced by users is preserved in the first stage, with RE allocation being considered in the second stage. An optimization approach built on a lattice model and a control algorithm based on nonlinear model predictive control theory is used to solve the two subproblems respectively. Similarly in [78], minimizing the electricity cost under electricity markets by joint power allocation and battery management for BS powered by hybrid energy sources and finite energy storages is studied. In addition to allocating RE, the energy demand of the BS is reduced by delaying some data when electricity price is high or when bad link quality is experienced. The problem is studied considering random data arrival, link quality, RE and variable grid energy price. Based on the Lyapunov optimization techniques, an on-line algorithm is designed to guarantee the worst delay experienced by users without the knowledge of future information.

These works are considered as a preliminary step, and are a basis for investigating the problem of mobile networks powered by RE in the Smart Grid environment. In Chapter 5 of this thesis, we study a novel behavior of BSs, where BSs provide ancillary services to the Smart Grid. Results show that this approach may lead to negative operational cost, where the Smart Grid pays to the network operator.

2.6 Performance metrics

Many metrics are used for evaluating the energy efficiency of cellular networks [6]. In addition, new ones are introduced to reflect the specificity of networks powered by renewable energy, where the choice of the metric(s) depends on the perspective of the study. In Figure 2.6, we present our classification of the used metrics and explain them in the following.

1. Economic metrics: The economic point of view is essential for the operators, where economical studies precede the decision of implementing RE in cellular networks. Examples: cost saving, operational cost, investment cost [16, 18, 44].

2. Environmental metrics: In order to evaluate the environmental profit of using RE. The percentage of reduced Carbon emissions is usually used as a reference [18].

3. Technical metrics: The technical states of different components of the system are usually studied to evaluate the performance of the system/algorithm. Special metrics are used for each component such as state of charge of the energy storage and maximum transmitted power time percentage of the BS [47, 44]. Mean depth of discharge is defined as the rate of the mean number of energy units consumed

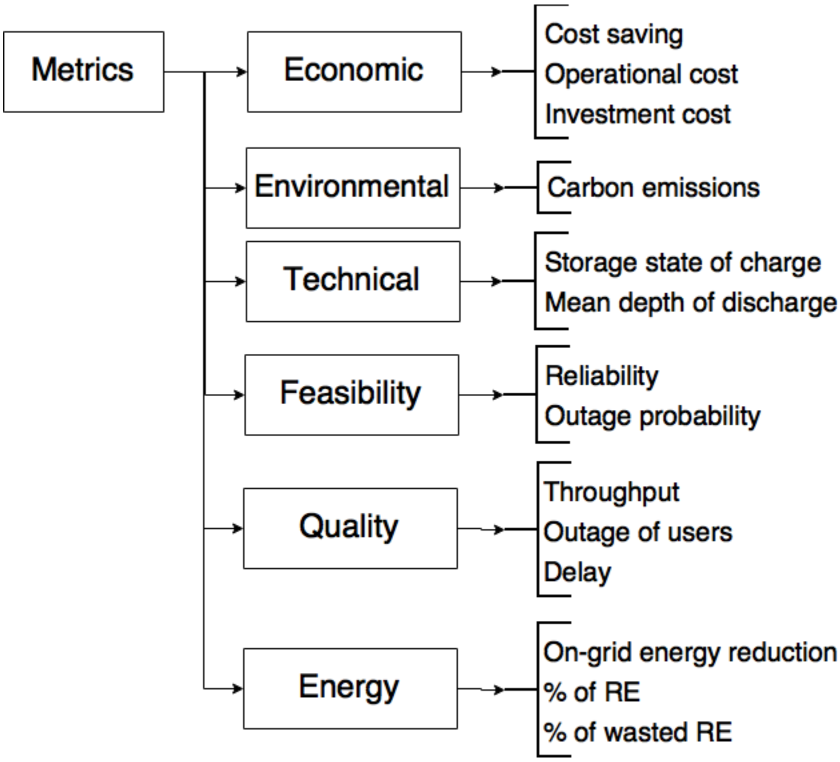

Figure 2.6: Classification of metrics used in evaluating the performance of cellular networks powered by renewable energy.

by the BS to the storage capacity of the battery bank [45]. Keeping the energy storage in the state of shallow charge or shallow discharge can effectively extend the storage life and then prolong the lifetime of the system.

4. Feasibility metrics: These metrics are used to evaluate the applicability of the system, such as reliability and availability in function of RE size and outage percentage in term of storage capacity [44, 47]. There are several definitions for Service outage probability (SoP) such as the probability that the energy state of the system is lower than a threshold (e.g. [45]) or the probability of not having enough energy to serve at least one user (e.g. [51]). The higher the value of the SoP is, the less reliable the system becomes.

5. Quality metric: A wide range of metrics can be used to evaluate the satisfaction of users. Classical metrics can be easily adopted to suit the study of REBS systems. For example degradation of throughput, percentage of users outage and throughput in terms of RE generation or component size (e.g. battery capacity) [5, 36, 66, 65].

6. Energy metrics: In general, energy metrics aims at evaluating the utilization of RE. However, the utilization of RE varies from one study to another. For example,

saved on-grid energy and percentage of renewable and non renewable energy used to power the system are used in [56, 41, 54]. Other definitions exist such as the rate of the total amount of RE stored in the battery bank and consumed by the BS to the total amount of harvested energy units in [45]. This metric can be also expressed as the percentage of wasted RE, due to storage efficiency and maximum capacity, to the total harvested energy.

2.7 Conclusion

In this chapter we surveyed the work done in the context of cellular networks powered by renewable energy. Then, we proposed a new renewable energy base station model and classified the previous work into several research sectors. The main tools and challenges for each sector are also presented. Specifically, we integrate the new approaches in the context of using renewable energy sources in powering cellular networks into a new framework. Finally, we presented the metrics used in evaluating the performance of cellular networks powered by renewable energy.

Based on the state of the art, we found that in contrast to off-grid BSs, where the aim is reducing their outage probability, the work on hybrid-energy BSs is open to many directions. More specifically, considering cellular networks powered by renewable energy in the Smart Grid environment was rarely tackled. The last idea is very promising given the evolution of the current power grid into the Smart Grid.

From technical point of view, the framework that we presented opens a lot of possibilities to increase the utilization of renewable energy. In our work we use energy management from the renewable energy stack and radio resource management and cell layout adaptation from the energy efficiency stack. Energy management can not be ignored when studying the adopted problematic. In fact, our preliminary work, presented in Chapter 3, proves that it is one of the important strategies and have significant effect on the performance of cellular networks. Moreover, radio resource management and cell layout adaptation approaches can bring high impact on the global energy savings for the cellular network.

In the following chapter, we present our classification of scenarios and objectives of using renewable energy in powering on-grid cellular networks. Then, we study the operation of base stations powered by renewable energy and the power grid considering real time price of on-grid energy.

CHAPTER 3 Cellular networks powered by renewable energy and the power grid

3.1 Introduction

While dealing with on-grid RE networks, most of the studies focus on decreasing the on-grid energy consumption. A further look on the state of art and the environment in which an on-grid REBS operates, we find that a classification of scenarios and objectives is essential to better utilize the generated RE. In this context, we propose in this chapter a new methodology for studying on-grid BSs powered by RE. We propose several objectives for using RE in powering on-grid BSs and identify the constraints that faces the network operators. As a first step, we propose a new algorithm for distributive operation of a BS powered by RE and the SG to minimize its energy operation cost.

3.2 Methodology of specifying the case study

On-grid BSs powered by RE are being deployed in different area types (urban, sub-urban, rural), infrastructure conditions and environments [7]. Consequently, utilizing RE may vary from one place to another. In order to better utilize the generated RE in a hybrid energy cellular networks (powered by the grid and local RESs), we propose a new methodology to analyze the deployment or operation parameters [26]. The steps of this methodology are presented in Figure 3.1 and can be summarized as: study the

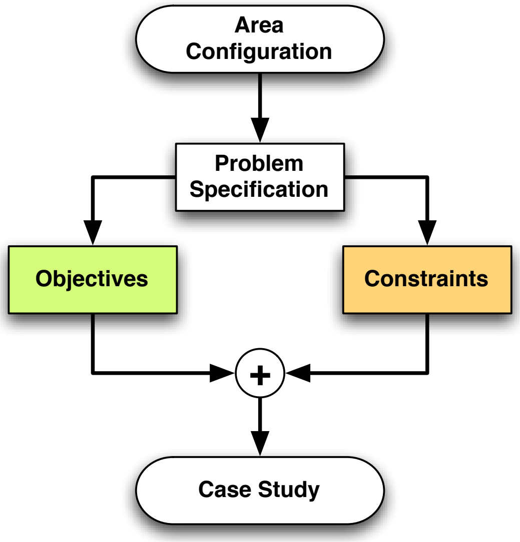

Figure 3.1: Specifying the case study of hybrid energy based cellular system.

area configuration; specify the problem; choose the objective(s); define the constraints; and study the case. These steps are detailed next.

3.2.1 Area configuration

The first step is to identify the characteristics of the area where the network (base stations) is deployed. Among these characteristic is the climate (e.g. solar insolation period, wind speed). This will lead to the right decision of the most convenient type of RE sources, and the correct dimensioning. The possibility of implementing the RE must also be studied, where the nature of the studied area (urban, sub-urban or rural) would directly affect the available free space to deploy the sources. For example, plenty of free space is usually available in rural sites, while the available space of urban sites is limited. Moreover, one of the major points in studying the area is the condition of the grid infrastructure. We distinguish between two main cases, Systematic Grid Failures Areas (SGFA) and Rare Grid Failures Areas (RGFA).

Systemic grid failure areas (SGFA) In these areas, mobile operators lack reliability of power grid which can experience frequent failures. Diesel generators are usually used as backup, which causes an increase in the cost and the carbon emissions. Examples of such areas can be found in Bangladesh and India. In this case, RE sources would replace the diesel generators and avoid the high fuel cost and logistics [14].

Rare grid failure areas (RGFA) In these areas, the power grid is reliable and grid failures occur only rarely. However, with the increase of energy demand it is critical to improve and integrate additional mechanisms to ensure the reliability of the grid (e.g. the evolution to Smart Grid). Moreover, the integration of RE is considered a strategical aim for some of these areas. Thus, using RE in powering BSs can play an important role in providing green communications and facilitating the integration of RE to the power grid while providing some profit to the mobile operator.

Islands The special nature of these areas introduces new constraints for the previous types. For example, energy generation is mainly based on fossil fuels and done in relatively small power plants or local generators. Thus, the typical energy prices are higher. As an example, the price of electricity in the island of Hawaii is more than twice the United States average [79]. RE sources are essential to increase the economic and environmental efficiency in this case.

3.2.2 Objectives of using RE

Due to different power grid conditions and different perspectives of mobile operators, RE usage might be directed in several ways. In Figure 3.2, we present some of the objectives of using RE in powering cellular BSs that are found in literature and propose several new ones. The details of each objective is presented next.

Decrease on-grid energy A frequent use of RE in cellular networks is to reduce on-grid energy consumption of the network [56]. As we show later, this objective does not reflect the real utilization of RE with the variation of grid conditions and parameters. Thus, more precise objectives that consider both the grid and the perspectives of the mobile operators should be defined.

Decrease carbon emissions Reduction of carbon emissions has been studied as a result of saving on-grid energy consumption [18]. Although there is a high correlation between the two concepts, reducing Carbon emission is not only related to the reduction of on-grid consumption. The type of on-grid electricity source is the most important factor. In other words, the grid's energy sources are different and each of them produces different amount of Carbon throughout the day. For example, if the energy sources of the grid are nuclear, the BS is encouraged to use the on-grid energy. However, the BS is encouraged to stop using on-grid energy and rely on its local RE sources if the sources are pollutants such as coal or oil generators.

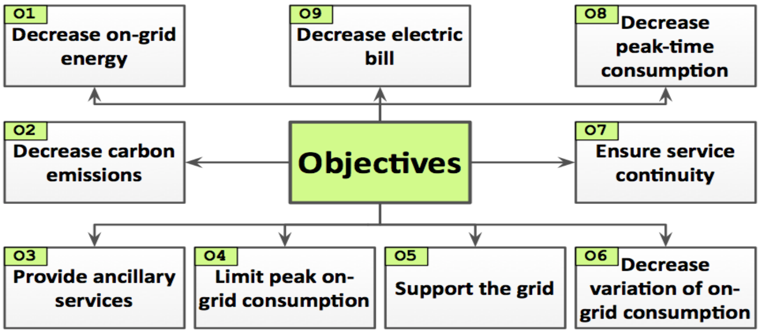

Figure 3.2: Objectives of using RE in hybrid energy based cellular system.

Limit the peak on-grid energy consumption Another possible objective is limiting the peak on-grid energy demand of the cellular network. This type of service will help the power grid in estimating the maximum energy demand, and dimensioning the infrastructure/previsions appropriately.

Support the grid In the past, matching the electricity supply to the demand was a challenging, but well defined problem. However, the problem is getting more complicated due to the continuing increase in the electricity demand and the changing nature of its characteristics. In this case, excess RE from a REBS may supply the grid to help satisfying the demand.

Decrease the variation of on-grid energy consumption The variation of mobile traffic over time results in variation of the network's energy demand. As a part of the power grid, this variation may cause instabilities to the power grid whenever it is under stress. Thus RE can be introduced to limit the variation of on-grid energy consumption.

Ensure the continuity of the system in case of grid failure In case of grid failure, the service faces large interruptions. This situation is not accepted by mobile operators, where they need continuous electrical power supply to ensure the non-stop function of the network. Usually operators rely on backup (diesel) generators as a solution for such condition. This is due to relatively low cost investment of these generators. However, the raise fuel prices, fuel transportation cost and even fuel hiking economically motivate the usage of RE sources. This, combined with the diminishing

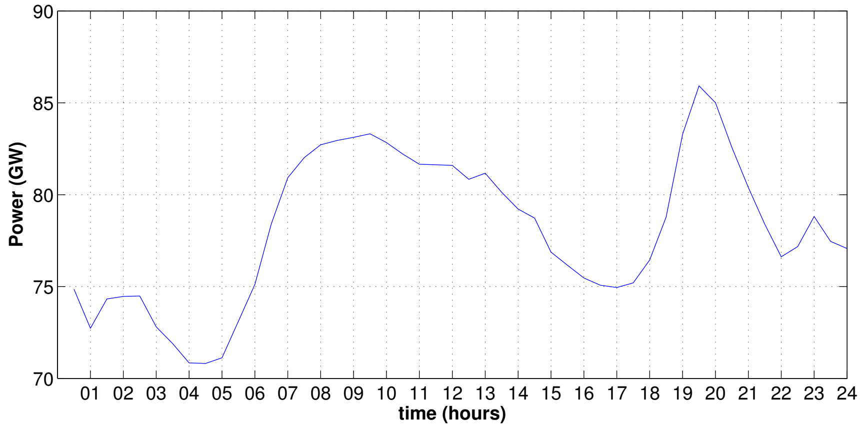

Figure 3.3: Grid energy demand variation through a day in France [24].

RE sources costs, motivate the objective of ensuring the continuity of service by using RE sources [16].

Decrease the peak-time consumption of the grid In general, the energy demand varies depending on the time and the nature of the area. In addition, the consumption of energy decreases significantly during night as shown in Figure 3.3, France power demand variation throughout a day, and increases significantly in some hours of the day. Moreover, the peak time of an industrial area is different to that of a residential one. Decreasing the consumption of energy at power grid's peak would support the grid at its critical time.

Decrease the electric bill One of the important motivations of using RE is economic one. With the right dimensioning of the renewable energy system (RESs and storage) and good operation and utilization of RE, the MNOs can significantly reduce the energy operational cost of their networks.

Provide ancillary services to the grid A more advanced service that can be offered by hybrid BSs is providing ancillary services. If the grid asks the mobile operator to decrease or stop the energy consumption from the grid for a certain time, the operator can respond by using the RE sources and the storages in order to react quickly. This will give benefits to the grid and profit to the operators.

Table 3.1: Suitability between objectives and areas' types.

Objective	O1	O2	O3	O4	O5	O6	O7	O8	O9
SGFA	Y	Y	N	Y*	N	Y*	Y	Y*	Y*
RGFA	Y	Y	Y*	Y	Y*	Y	N	Y	Y
Islands of SGFA	Y	Y	N	Y*	N	Y*	Y	Y*	Y*
Islands of RGFA	Y	Y	Y*	Y*	Y*	Y*	N	Y	Y

Y: Objective and area type are compatible.
N: Objective and area type are not compatible.
Y*: Probably compatible, but further studies are necessary.
Objective number (e.g. O1) corresponds to the number in Figure 3.2.

3.2.3 Suitability between objectives and area configuration

In addition to the area configuration, choosing the objective(s) depends on the operator's perspectives and engagements. In SGFA the highest priority objective is to ensure the continuity of service. However, and depending on the size of RE and occurrence, duration, and type (scheduled or not) of the power grid failure, the cellular operator can benefit from using RE to achieve any of the other possible objectives, such as decreasing the electric bill. We can find high correlation between decreasing the electric bill and reducing carbon emissions. Both of the objectives can be achieved by avoiding the use of diesel generator and decreasing the on-grid energy.

In contrast to SGFA, RGFA does not often suffer from grid failures and thus service continuity is not the major concern. However, each of the objectives needs special investigation. For example, ancillary services cannot be provided in any location (e.g. the power grid should have some capabilities considered part of the Smart Grid). Moreover, supporting the grid is related to the energy demand for serving the users and the rate of RE generation. In islands, decreasing the electric bill appears as high priority objective, however other objectives may be introduced. Generally, operator's profit is one of the main factors in deciding the objective(s). Table 3.1 provides a summary of the suitability between objectives and types of areas.

Supposing the suitability of the objective with the area configuration, the form of the objective may be translated differently with each configuration. For example, decreasing the electric bill in RGFA with variable energy price is different than in areas where the energy unit price is constant. In the second case, decreasing the electric bill is identical to decreasing the on-grid energy, since the price is the same for the whole

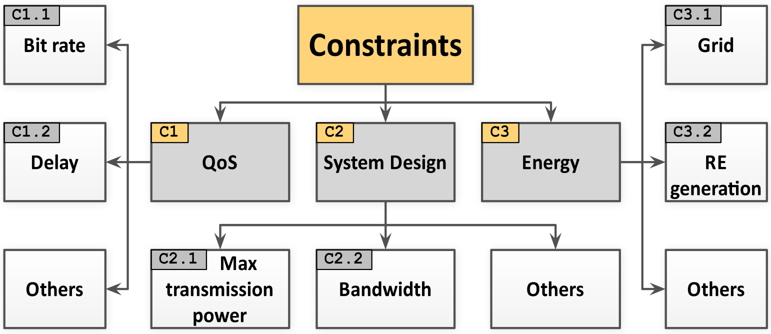

Figure 3.4: Different Constraints in hybrid energy based cellular system.

day. Moreover, we can find a significant correlation between decreasing the electric bill, decreasing the consumption of energy at the peak and decreasing the carbon emissions in variable energy price areas, where the price of energy increases with the demand until it reach the maximum at the peak time. In the same time, temporary pollutant generators are used to satisfy the energy demand. It must be noted that grid energy can be provided from non pollutant sources such as RE farms or nuclear plants[1].

3.2.4 Constraints

After studying the area configuration and choosing the objective(s), we need to specify the constraints of the problem. These constraints must be well defined to have a realistic scenario and obtain a good solution. The constraints are classified as shown in Figure 3.4.

Quality These kinds of constraints are specified to ensure the satisfaction of users. Typical QoS constraints used in studying cellular networks can be used such as bit-rate and delay. However, these constraints can vary from one place to another based on the demand of the users in the target area.

System Design These constraints depend on the chosen cellular network technology. They usually appear as hard constraint in the problem formulation. For example, the maximum transmitted power and available resources (bandwidth) are related to the type and hardware design of the BS.

[1]Even though nuclear power plants do not produce CO_2, it has other types of pollution.

Energy The previous types of constraints are typical in studying cellular networks. However, dealing with RESs and the grid introduce a new type of constraints related to energy availability. These constraints reflect the grid conditions, generation rate of RE and storage characteristics. If the grid is not able to satisfy the full demand or suffers failure then several constraints would appear in the problem formulation. Moreover, the time and rate of RE generation limit its availability. Finally, the capacity and efficiency of the used storage affects the possibility of storing energy.

3.3 Energy operational cost

Reducing the energy operational cost is the highest priority for the network operator. When considering on-grid energy sources in developed countries (RGFA), the main source of energy is the power grid. Although decreasing the grid energy will lead to the reducing the energy cost, it is not necessarily the best strategy to follow. This due to the evolution of the power grid and introducing dynamic tariff systems.

3.3.1 Dynamic tariff of energy price

The technical and economic evolution of the current power grid and the increase in the energy demand promote dynamic tariff systems to achieve better management of the grid. In return, it enables cost saving to customers who are willing to participate and follow a good energy management strategy.

In contrast to traditional fixed electricity price, dynamic tariff corresponds to the time-based variation of the electricity price. Besides grid management support and cost reduction of the customers, responsive demand based on the grid condition leads to the reduction of greenhouse gases and local pollutants. Enhanced price signals can cause customers to shift demand away from peak times, and thus avoiding the activation of emission-intensive generators. In the following we present the main dynamic tariff programs.

Time Of Use (TOU)

TOU is a program that rates the price of electricity depending on the period of the day [80]. The goal is to allow users to adapt their consumption to flatten the energy load curve by reducing demand for on-peak periods and increasing for off-peak periods. Figure 3.5 presents the Baltimore Gas and Electric TOU pricing for a day. Electricity prices paid for energy consumed are pre-established and known to consumers in advance, allowing them to vary their usage in response to such prices and manage their energy costs.

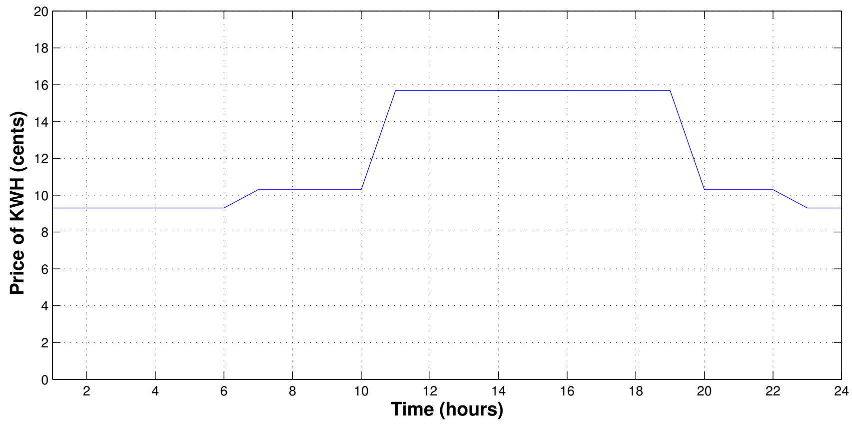

Figure 3.5: An example of time-of-use pricing program provided by Baltimore Gas and Electric [80].

Critical Peak Pricing (CPP)

CPP is in essence a form of TOU programs except that CPP is even more targeted [80]. Instead of daily on-peak times as in TOU rate structures, the on-peak times are limited to just some days of year when demand is expected to be the highest, such as during heat waves when the entire population runs their air conditioning. The primary goal of the program is to shift load from on-peak to off-peak hours on these peak demand days. CPP rate plans typically designate a specific time window for the CPP tariff, such as between 2pm and 7pm. Participants in this rate program are offered discounted on the price of energy during off-peak hours in return for being charged much higher rates during critical hours. CPP on-peak rates typically range between 400% and 700% of the off-peak electricity rate [80]. In this type of pricing, participants are notified ahead for the rates and events. Figure 3.6 shows an example of CPP of electricity for a day in the state of California.

TOU/CPP pricing

One of the disadvantage of TOU rates is its inability to create additional incentives on high system stress days, such as peak event days that CPP programs intentionally target. The ability of dealing with such conditions in CPP pricing is due to the large difference between on- and off-peak pricing in this program. However, CPP is not

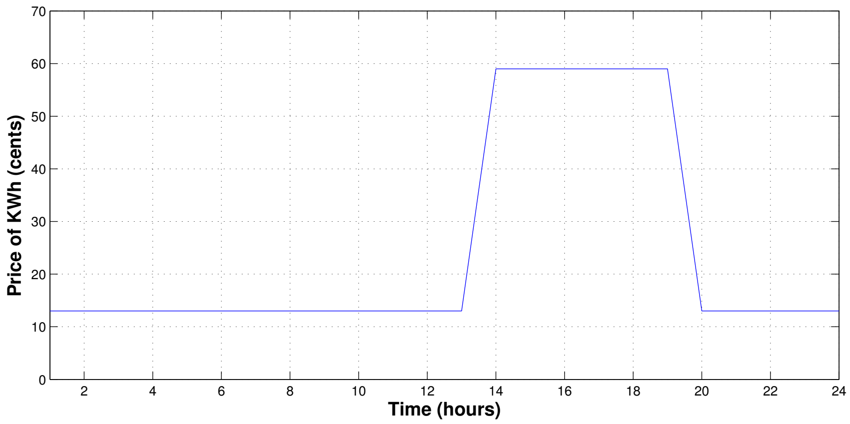

Figure 3.6: An example of Critical peak pricing of electricity used in the state of California [80].

designed to deal with daily variation of normal days. A hybrid strategy between TOU and CPP, denoted TOU/CPP, can reflect the daily variations and reply to special events.

Real Time Pricing (RTP)

The TOU/CPP rates may be adopted as a solution for the early stage of the Smart Grid development [81]. However, these pricing strategies do not reflect the true cost of power that occurs within a fixed period due to outages or short term energy load variation. With RTP, customers are charged by the actual real-time costs of electricity production based on supply and demand. The price of electricity moves with the peaks and allow robust reflect to the dynamics even when there is unpredictable energy demand in the grid. Technological advances in metering infrastructure and wireless communication technology have created the ability to communicate real-time electricity price information to its customers, where price signal is provided whenever the price changes. An example of the real-time price of electricity is found in Figure 3.7

3.3.2 Case study

We apply the methodology we propose in Section 3.2 to a city in France (Marseille), where systematic grid failures are not typical (e.g. an RGFA). Moreover, due to the weather conditions of Marseille, there is a high solar energy potential that can reach 6.8 kWh/day/m^2 [82]. Thus, we can use solar panels as the RES. Taking into consideration the urban nature of the city, the size of solar panels must be limited. As

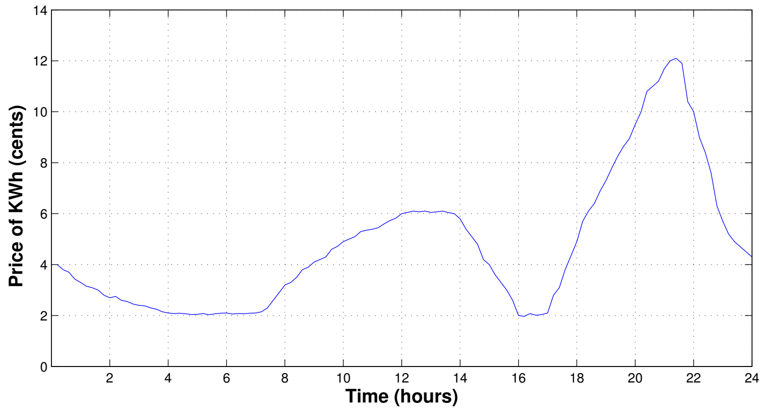

Figure 3.7: An example of real time pricing of electricity used for a day in France [24].

an objective, we adopt decreasing the electric bill of the cellular network by using RE and considering real time price of electricity.

Although we take the city of Marseille as the case study, the results that we present are generalizable. The difference between two locations in terms of solar energy generation is the total amount of generated energy, condition of generations (e.g. clouds) and period of generation. Moreover, the amount of generated solar energy depends on the size of solar panels. In our simulation, we variate the amount of generated renewable energy in terms of the base station demand and we use different patterns corresponding to different months of the year.

Problem formulation

The problem is to decide when the BS should use the available RE and when to store it for later usage. We consider a network of LTE BSs, where the operator pays the real-time price of electricity. To simplify the work we suppose that each BS takes the decision of using RE periodically, where we decompose the time into stages with duration T. In this study, we only use energy management technique to enhance the utilization of RE. On one hand, this will allow distributed operation of BSs without the need for cooperative strategies between them. On the other hand, this would show the effectiveness of energy management and the necessity of using it whenever considering RE in powering on-grid BSs. For each BS, the optimization problem can be expressed as:

$$min(\sum_i Cost_i) \tag{3.1}$$

$$subject\ to:$$

$$Quality\ constraint:$$

$$R_j \geq R_{thr} \quad \forall j \forall M \tag{3.2}$$

$$System\ constraints:$$

$$\frac{\sum B_j}{B_{max}} \leq 1 \tag{3.3}$$

$$P_i \leq P_{max} \tag{3.4}$$

$$Energy\ constraint:$$

$$E_i \leq Es_i \tag{3.5}$$

where all calculations refer to the stage i, Equation 3.1 represents the objective of reducing the energy operational cost $Cost_i$, which corresponds to the cost of grid energy, $Cost_i = T \times P_i^g \times Price_i$, P_i^g is the grid power consumed by the BS, $P_i^g = P_i - P_i^r$, P_i is the BS power demand, P_i^r is the power taken from renewable sources, $Price_i$ is the price of the energy unit, R_j is the bit rate of user j, M is the set of users associated to the BS, R_{th} is the threshold bit rate, B_j is the allocated bandwidth for user j, B_{max} is the total bandwidth of the BS, P_{max} is the maximum input power (due to maximum transmitted power), E_i is the allocated RE, Es_i is the available energy in the storage at the beginning of the stage i where $Es_i = Es_{i-1} + Eh_{i-1} - E_{i-1}$, Eh_i is the harvested energy, taking into consideration the loss due to storage efficiency when exists.

The first constraint, Equation 3.2, represents the quality constraint to ensure the satisfaction of users by providing a minimum bit rate. The system constraints appears in the form of hard constraints related to the BS design as shown in Equations 3.3 and 3.4. Equation 3.5 represents the energy constraint where the allocated energy for a stage i should be less than the available energy in the beginning of this stage.

Proposed algorithm

Our aim is to prove that intelligent energy management of harvested energy will result in higher electric bill reduction than traditional one and that the problems of saving on-grid energy and reducing the electric bill are not identical in a variable price environment. Moreover, we consider several cases for the storage system: 1) no battery 2) ideal battery 3) real battery.

For the three case we apply a traditional greedy algorithm, i.e. use RE whenever it is available. In case of existence of battery, excess RE is stored and then used directly in case of shortage of RE. The major motivation for using the traditional algorithm is its simplicity. However, this algorithm does not take into account the grid energy price at different times. In order to benefit more from generated RE, we propose a simple heuristic algorithm which takes the decision to use RE or store it based on the on-grid energy price and the state of the battery. We preserve the simplicity of the traditional algorithm and avoid high complexity algorithms by proposing a simple extension taking into account the real-time electricity price, the Simple Price-Aware Electricity Management Algorithm (SPAEMA). We quantify each of the storage states and the price into 3 levels: low, medium and high. Table 3.2 shows the applied decisions for different cases.

Table 3.2: Decision of SPAEMA for different cases of battery and price.

Battery/price	Low	Medium	High
Low	store	store	use
Medium	store	use	use
High	use	use	use

The algorithm is designed to store the RE in case of low price and then use at the high price. Moreover, it takes into account the level of the storage to avoid energy wastage due to storage unavailability (e.g. full storage). It is worth mentioning that this algorithm can be also adopted for any dynamic tariff. However, in contrast to RTP the price of electricity in TOU or CPP is known in advance and depends on the period of the day. In this case, the decision would depend on the storage state and time of the day.

System model

We consider a macro LTE BS of 2 GHz carrier frequency and 10 MHz bandwidth. We adopt cost 231 Walfisch-Ikegami for path loss [83] and consider the noise figure as 9 dB. Moreover, we assume that the shadowing is lognormal with 8 dB standard deviation. The users are uniformly distributed over an area of radius Ra. The average number of users is obtained from [84], and a user is considered satisfied when achieving $1Mb/s$ bit rate. The bit rate calculation is based on [85].

Concerning the RE generation, we vary the total amount of generated energy, as a percentage of the BS demand, to show its effect on the energy operational cost. It is possible to present the results in function of the area of solar panels. However, the area of solar panels that generate specific amount of energy varies from one location to another. Moreover, we consider different periods of RE generation, which corresponds

Table 3.3: Parameters and assumptions.

parameters	values and assumptions
Carrier frequency	2GHz
Bandwidth	10MHz, FDD
Maximum transmitted power	43dBm
Radius (Ra)	1000m
PRB	50
PRB bandwidth	180 KHz
User distribution	uniform
maximum number of users	18
User Bit rate	1 Mb/s
Path loss	Cost 231 Walfisch-Ikegami
Scheduler	round robin
Noise figure	9 dB
BS Power model	Earth [60]
Generated RE (%)	25%, 50%, 75%
storage capacity (kWH)	3, 6, 9
Lognormal shadowing	standard deviation 8 dB
Number of stages L	120

to different months of the year. The efficiency of the storage is 90% as considered in [18]. The parameters and assumptions of the system are presented in Table 3.3.

3.3.3 Results and discussion

In this section, we present the results of simulating the traditional and SPAEMA algorithms. The presented behavior of the base stations are based on on-grid energy price variation presented in Figure 3.7 and renewable energy generation presented in Figure 3.8. However, the results presented in Figure 3.9 are the average obtained by varying the distribution of users, renewable energy pattern and on-grid energy price variation. Figure 3.9 shows the cost reduction for different cases of traditional and SPAEMA algorithms with respect to RE generation. The total amount of RE generation in the day is presented as percentage of BS total energy demand. The capacity of storage used are 3, 6 and 9 kWh for 25%, 50% and 75% of RE generation respectively.

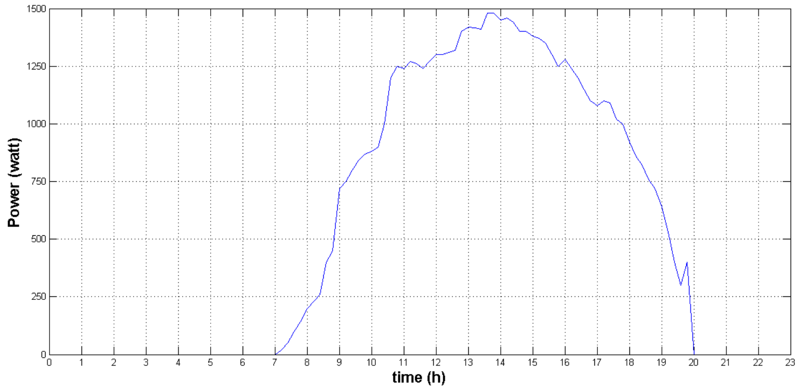

Figure 3.8: Pattern of renewable energy generated by solar panels.

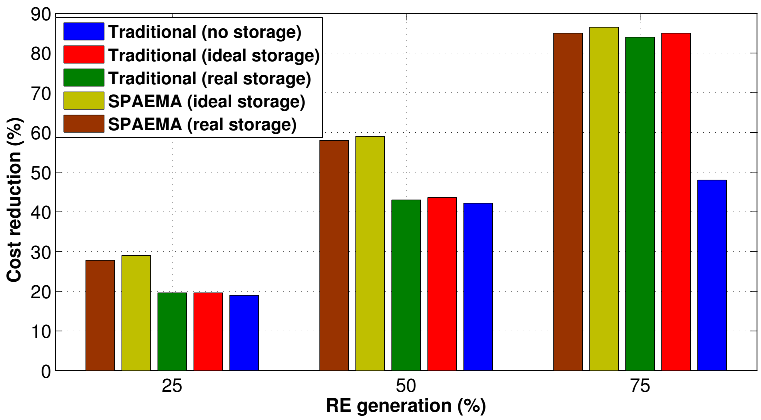

Figure 3.9: Cost reduction for different cases and RE generations (in terms of BS demand).

The percentage of cost reduction as function of time for the traditional algorithm (RE generation is 50%) through a day is shown in Figure 3.10. The three cases of traditional algorithms have the same performance in the beginning. In case of excess of RE generation, the storage (when there is such) is charged (otherwise excess energy is lost). This explains the longer period of cost reduction in case of existence of storage (battery). However, the case of ideal battery is very close to that of real battery, where the total cost reduction is almost the same. The existence of storage is not essential in case of traditional algorithm for low RE generation. We can see that the traditional algorithm achieve almost the same cost reduction when RE generation is 25% and 50% of energy demand with and without the storage. However, introducing energy storage leads to significant cost reduction when RE generation increases to 75% of the BS energy demand compared to the case where storage does not exist.

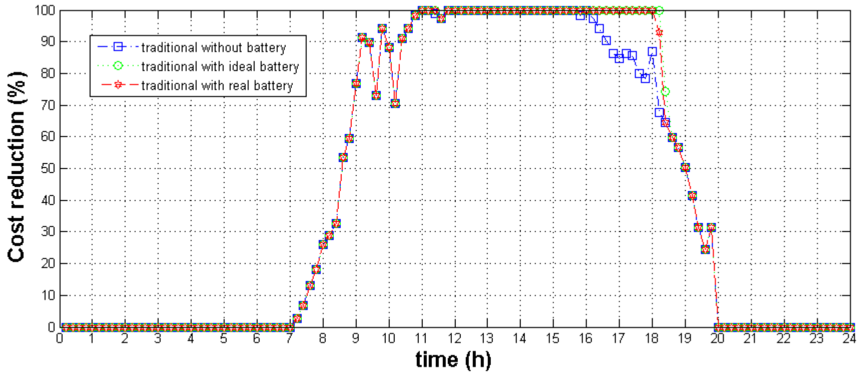

Figure 3.10: Percentage of cost reduction for traditional algorithm through a day.

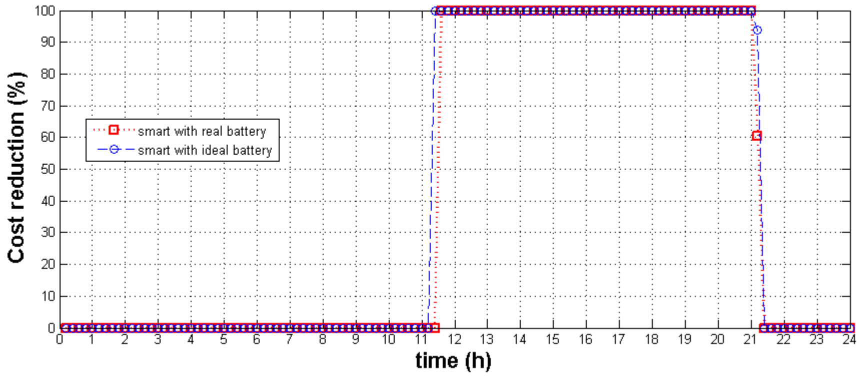

Figure 3.11: Percentage of cost reduction for SPAEMA through a day.

Based on cost reduction of traditional algorithm in Figure 3.10, RE generation in Figure 3.8 and price variation in Figure 3.7, we notice that the main cost reduction is in the periods when there is RE generation. However, the price of electricity is higher in the periods when RE is not available. Traditional algorithm is saving on-grid energy but not at the time of highest price. In contrast, SPAEMA does not use the generated energy directly, instead energy is stored and then used when the price is high as shown in Figure 3.11.

The percentage of RE lost (case of RE generation equal to 50%) due to storage efficiency using SPAEMA (3% loss) is higher than the case of traditional algorithm (0.5% loss). This is because SPAEMA tends to store energy more than traditional algorithm. Thus the traditional algorithm saves more on-grid energy than SPAEMA. However, SPAEMA increases the total energy cost reduction to achieve 58% in case of real battery (storage), which outperforms the traditional algorithm by 15 points (58% vs 43%). These results justify the efficiency of the proposed algorithm in utilizing the

RE and that the objective of reducing the electric bill is different than saving on-grid energy.

To evaluate the effect of the efficiency of the storage, we compare the performance SPAEMA for in real and ideal storage cases. When RE generation is 50% of the energy demand, RE lost due to the efficiency of the storage leads to lower cost reduction to the case of ideal one (58% vs 63%). This difference is less significant when RE is 25% and 75% of the BS demand. In the first case, this is due to lower loss due to less storing of energy. In the second case, more energy loss occurs due higher energy storing. However, enough energy is stored to be used at high/ medium price. Finally, we should note that as much as RE generation increases to approach the energy demand of the BS, the performance of SPAEMA and the traditional algorithm get closer. This is because the margin of deciding the usage of RE get smaller.

3.4 Conclusion

In this chapter, we presented our methodology to identify the scenarios and objectives of using renewable energy in powering cellular networks. We focused on minimizing the energy operational cost of a base station powered by renewable energy and the power grid. In this context, we explain dynamic tariff programs proposed by the grid. We present our algorithm for managing the renewable energy consumption considering real time price of on-grid energy. The results verify the effectiveness of our algorithm, where it achieves lower on-grid energy consumption but higher cost reduction compared to traditional greedy algorithm. On one hand, this validates that the objectives of reducing the on-grid energy and energy operational cost are different. On the other hand, the importance of a good energy management is verified when using renewable energy in powering on-grid base stations.

In the following chapter, we extend this work by minimizing the energy operational cost of a network of base stations. In addition to energy management, we study the effect of cell layout adaptation and radio resource management on the performance of the network.

CHAPTER 4 Proposed algorithm for Electric bill Reduction

4.1 Introduction

In the previous chapter we verified the need for a good energy management when powering base stations with renewable energy sources. However, the approach we considered in Chapter 3 did not take into consideration neither the possible cooperation between base stations nor the effect of interference between base stations. In this chapter, we consider the problem of reducing the energy operational cost of a network of macro- base stations. Macro base stations are considered due to their high energy demand. Moreover, they have the highest impact on the network energy performance as shown by many studies, such as [51] and [18]. We start by presenting the problem formulation of minimizing the energy operational cost of a network of macro- base stations. Then, we describe our proposed algorithm that determines the usage of renewable energy, switches-off base stations, adjusts the transmitting power of base stations and chooses the number of active resource blocks of each base station. After discussing the effect of our algorithm, we study the impact of adding renewable energy powered small cells on the energy cost reduction of the network.

4.2 Problem formulation

We consider a cellular network composed of N BSs serving a set of mobile users M. A BS is either REBS, i.e. it has its own local RESs, storage system and is connected to the grid, or a BS that is only connected to the grid but is willing to cooperate with other BSs.

The network can adjust its configuration to increase the utilization of RE and achieve the predetermined objective(s) by:

- Allocating and re-allocating RE.
- Switching-off some BSs.
- Changing the transmitted power of BSs, where we consider discrete values for the transmitting power.
- Determining the number of active resource blocks for each BS.

Allocating RE is the process of deciding whether to store or use the harvested energy. Re-allocating RE is changing the amount of allocated RE based on the change in the network configuration. Switching-off BSs is done based on the RE availability and traffic load. Similarly, adjusting the transmitted power of BSs is done to adapt the network configuration to the availability of RE at each BS. Finally, determining the number of activated resource blocks is done to avoid energy wastage due to excess of resource blocks. These processes are limited by several constraints related to energy availability, users QoS and system design.

We consider an interval of time divided into p periods each of duration T. The period length T should be chosen carefully – small enough to react to changes in the conditions (*precision*) and big enough to avoid high complexity and ensure the stability of the system (*computability*). Harvested RE is stored in the storage and then allocated to each BS at instant t_i corresponding to the beginning of period T_i. We assume that BSs always have data to transmit. Thus, BSs are always transmitting, and this corresponds to the worst case scenario with respect to interference experienced by the users. Moreover, interference experienced by a stationary mobile in the network is constant over time. For a network of BSs, the problem of minimizing the energy operational cost in a real time price environment can be expressed as follows:

$$min(\sum_{b,i} Cost_{b,i}) \tag{4.1}$$

$$subject\ to:$$

$$Quality\ constraint:$$

$$R_{j,b} \geq R_{j,thr} \quad \forall\, j\, \epsilon\, M \tag{4.2}$$

$$System\ constraints:$$

$$\frac{\sum_j n_{j,b}}{n_{b,max}} \leq 1 \quad \forall\, b\, \epsilon\, [1, N] \tag{4.3}$$

$$P_{b,i} \leq P_{b,max} \quad \forall\, b\, \epsilon\, [1, N] \tag{4.4}$$

$$Energy\ constraint:$$

$$Ea_{b,i} \leq Es_{b,i} \quad b \,\epsilon\, [1, N] \tag{4.5}$$

where all calculations refer to BS b in period i. $Cost_{b,i}$ is the on-grid energy cost where $Cost_{b,i} = T \times P^g_{b,i} \times Price_i$, $P^g_{b,i}$ is the grid power consumed by the BS and $P^g_{b,i} = P_{b,i} - P^r_{b,i}$, $P_{b,i}$ is the power demand of the BS, $P^r_{b,i}$ is the power taken from renewable sources (energy storage), $Price_i$ is the energy unit price, $R_{j,b}$ is the bit rate of user j associated to BS b and is calculated following modified Shannon formula presented in [85] and expressed in equation 4.6.

$$R_{j,b} = n_{j,b} \times BW_{RB} \times BW_{eff} \times log_2(1 + \frac{SNIR_j}{SNIR_{eff}}) \tag{4.6}$$

$n_{j,b}$ is the allocated resource blocks by BS b to user j, BW_{RB} is the bandwidth of a resource block, BW_{eff} is the bandwidth efficiency, $SINR_j$ is the signal to interference plus noise ratio of the user j, $SINR_j$ is expressed as follows:

$$SINR_j = \frac{Pr_{j,b}}{N_{j,b} + I_{j,b}} \tag{4.7}$$

$Pr_{j,b}$ is power received by user j from BS b. $N_{j,b}$ is the terminal noise and is defined as:

$$N_{j,b} = K \times Tem \times n_{j,b} \times BW_{RB} \tag{4.8}$$

K is the Boltzmann constant, Tem is the temperature in Kelvin. I is the interference and is calculated as the sum of the received power of the first tier of neighbour BSs. $SINR_{eff}$ is the SINR implementation efficiency of LTE. $R_{j,th}$ is the minimal (threshold) bit rate guaranteeing the QoS, $n_{b,max}$ is the total number of available resource blocks and is related to the system design of the BS, $P_{b,max}$ is the maximum input power, $Ea_{b,i}$ is the allocated RE for BS b in i^{th} stage, $Es_{b,i}$ is the available energy in the storage of BS b at beginning of i^{th} stage and $Es_{b,i} = Es_{b,i-1} + Eh_{b,i-1} \times S_{eff} - Ea_{b,i-1}$, $Eh_{b,i-1}$ is the harvested RE during period $i-1$ and S_{eff} is the energy storage efficiency.

The power model of the BS follows the EARTH model [60]. The power demand (input power) of BS b in period i consists of a static part $P_{b,0}$ and a load dependent part related to the transmitted power $P_{T_{b,i}}$. The transmit power can contribute a portion of up to 43 % (for macro BSs) of the total BS power demand [60]. Moreover, the power demand depends on its number of active resource blocks. It can be expressed as:

$$P_{b,i} = N_{b,trx} \times (P_{b,0} + \frac{n_{b,i}}{n_{b,max}} \times \Delta P_b \times P_{T_{b,i}}) \tag{4.9}$$

where $N_{b,trx}$ is the number of transceiver chains of BS b, $n_{b,i}$ is the number of active resource blocks and ΔP_b is the slope of the load dependent power part. The BS is active if at least one user is associated. If not, the BS will switch into sleep mode and the input power of such BS is as follows:

$$P_{b,i} = N_{b,trx} \times P_{b,sleep} \tag{4.10}$$

where $P_{b,sleep}$ is the sleep mode power demand.

Reducing the energy operational cost requires the analysis of different factors affecting the adjustment of network configuration. Parameters, such as availability and generation of RE, on-grid energy price variation and traffic intensity, vary with time making the problem more complicated. To reduce the complexity of the problem, we decompose it into several sub-problems as follows.

4.2.1 Renewable energy allocation

For each BS, the amount of RE at each period should be allocated carefully to maximize the utilization of RE. The amount of allocated RE in a period is affected by the RE generation and allocation in previous periods and will affect the allocation in the following ones. Moreover, the utilization of allocated energy of each BS is affected by the allocated RE for the rest of the BSs. In [56], the problem of maximizing the utilization of allocated RE is formulated as follows:

$$max \ \sum_{b,i} U_{b,i}(Ea_{b,i}, Ea_{/b,i}) \tag{4.11}$$

$$subject\ to:$$

$$Ea_{b,i} \leq Es_{b,i} \tag{4.12}$$

where $U_{b,i}$ represents the utilization of the allocated RE in terms of the saved on-grid energy for BS b in the period i, $Ea_{b,i}$ represents the allocated energy, $Ea_{/b,i}$ represents the allocated energy for all BSs except b. However, this model represents the utilization of allocated RE in the objective of minimizing the on-grid energy. To generalize it, the objective(s) of using RE must be translated and represented by its (their) corresponding parameter(s). Hence, the objective of the problem can be expressed as:

$$max \ \sum_{b,i} U_{b,i}(Ea_{b,i}, Ea_{/b,i}, o_1, o_2, \dots) \tag{4.13}$$

where $o_1, o_2, \dots$ represent the objectives parameters. In the case of mature energy markets, the price of electricity depends on the period of the day. Thus, the energy unit price can be used as an objective parameter for the electric bill reduction problem (reducing the energy operational cost). The new optimization problem of RE allocation can be expressed as:

$$max \sum_{b,i} U_{b,i}(Ea_{b,i}, Ea_{/b,i}, Price_i) \tag{4.14}$$

$$subject\ to:$$

$$Ea_{b,i} \leq Es_{b,i} \tag{4.15}$$

4.2.2 Energy consumption minimization

Knowing that the period T is short enough, the price of on-grid energy unit is constant throughout the period. Thus, reducing the electric bill of the operator is equivalent to minimizing the on-grid energy consumption during the same period. We can express the on-grid energy consumption minimization problem as follows:

$$min(\sum_{b} G_{b,i}) \tag{4.16}$$

$$subject\ to:$$

$$Quality\ constraint:$$

$$R_{j,b} \geq R_{j,thr} \quad \forall\, j \,\epsilon\, M \tag{4.17}$$

$$System\ constraints:$$

$$\sum_{j} n_{j,b} n_{b,max} \leq 1 \quad b \,\epsilon\, [1, N] \tag{4.18}$$

$$P_{b,i} \leq P_{max} \quad b \,\epsilon\, [1, N] \tag{4.19}$$

where $G_{b,i}$ represents the on-grid energy consumption of BS b in period i. Like [56], we assume that the BS uses RE if the allocated RE is enough to supply the BS for the entire period. Otherwise, the BS will consume on-grid energy. This means that the BSs will be powered by either RE or the grid, and $G_{b,i}$ is expressed as:

$$G_{b,i} = \begin{cases} 0, & Ea_{b,i} \geq D_{b,i} \\ D_{b,i}, & otherwise \end{cases} \tag{4.20}$$

where $D_{b,i}$ is energy demand of BS b for period i, $D_{b,i} = P_{b,i} \times T$. This problem can be translated into minimizing the number of BSs that consume on-grid energy.

4.2.3 Radio resource allocation

The cell size of a BS depends on several parameters one of the major being the amount of allocated/available RE. Thus, we expect to have BSs with different cell sizes, and consequently different number of associated users. For BS b, the number of associated users $m_{b,i}$ in period i depends on the density of the users d, traffic intensity l_i and the area of the served cell $A_{b,i}$. It can be expressed as:

$$m_{b,i} = d \times l_i \times A_{b,i} \tag{4.21}$$

During a period T_i, the density of users and the traffic intensity of an area are steady. Thus, the number of associated users to each BS depends on the area of the served cell. However, the RE availability and allocation may lead to having cells with different sizes and different number of associated users. As a consequence, the network needs a radio resource allocation (RRA) scheme to avoid excess of active radio resource blocks, especially for cells with small coverage area. Otherwise, excessive energy consumption would appear based on the power model presented in Equation 4.9. The reduction of energy demand due to RRA decreases the on-grid energy consumption of BSs and would allow them to rely on RE if the energy demand matches the allocated RE. In the same way, RE is saved for future allocation in case of BS relying on RE. For each BS b, we propose to reduce the number of active resource blocks $n_{b,i}$, while preserving the users QoS. The problem can be expressed as:

$$min\;(n_{b,i}) \tag{4.22}$$

$$subject\;to:$$

$$R_{j,b} \geq Rj_{,thr} \quad \forall j \epsilon M \tag{4.23}$$

We should note that the transmitting power for each BS is determined during the phase of energy consumption minimization and remain unchanged during this stage.

4.3 Problem complexity

An algorithm is a step-by-step procedure for solving a computational problem [86]. For a given input, it generates the output after a finite number of steps. The time complexity (or the running time) of an algorithm expresses the total number of elementary operations, such as additions, multiplications and comparisons, for each possible problem instance as a function of the size of the instance. In this section, we analyze the complexity of the problem of on-grid energy minimization presented in Section 4.2.2.

In the field of cellular networks, the set cover problem often appears such as in BS switching-off [87], interference management [88] and radio network planning [89].

To analyze our problem, we first start by defining the set cover problem [90].

Definition 1. *Given a universe* U *and a set of subsets of* U, $S = \{S_1, S_2, \cdots, S_n\}$ *where* $S_i \subset U \quad \forall i = 1, 2, \cdots n$, *such that the unions of these subsets is* U, *i.e.* $\cup_{S_i} = U$ *. A cover is a subfamily of sets* $C \subseteq S$ *whose union is* U, *i.e.* $\cup_{S_i \in C} S_i = U$. *Finding the cover with minimum size is known as the set cover problem, which is NP-hard problem [90].*

.

An example of the set cover problem is as follows. Consider a universe $U = \{1, 2, 3, 4, 5\}$ and the set of sets $S = \{\{1, 3\}, \{1, 2, 3\}, \{2, 4\}, \{3, 4\}, \{4, 5\}, \{5\}\}$. The union of S is U. However, we can cover all the elements by smaller number of sets. The smallest number of sets that can cover the universe in this case is 2 and the sets are: $\{1, 2, 3\}$ and $\{4, 5\}$.

Consider the problem of minimizing the on-grid energy in Section 4.2.2. In this case we only deal with BSs relying on the grid and users not covered by BSs relying on RE. Instead of considering multiple transmitting power, we simplify the problem into minimizing the number of active on-grid BSs, where each BS can be in two states: ON or OFF. Assuming that $U = \{u_1, u_2, \cdots, u_M\}$ is the universe, where each element of U corresponds to a user in the network (M is the number of users), and $S = \{BS_1, BS_2, \cdots, BS_i, \cdots, BS_N\}$ is the set of subsets, where each subset i corresponds to the set of users covered by a given BS i (N is the number of base stations), minimizing the number of active BSs is equivalent to finding the smallest cover for S. We can see that the simplified version of the problem presented in Section 4.2.2 has similar characteristics to the set cover problem. Thus, we have the conjecture that our problem is NP-hard.

4.4 Proposed algorithm

Due to the high complexity of the problem, we propose a heuristic algorithm described in this section for minimizing the energy operational cost of the network. At the beginning of each period, we apply our algorithm, denoted electric bill reduction algorithm (EBR), to adjust the network's configuration starting from its default configuration, i.e. all BS are active transmitting at maximum power with maximum active resource blocks (all resource blocks are active). The matrix of association and possible association of each user with the corresponding BS(s) are determined based on the acceptable bit rate guaranteeing the QoS.

The proposed algorithm is presented in Algorithm 1 and the main processes of the algorithm are described in the following.

4.4.1 Switching-off base stations

The price of electricity is constant during a period, thus reducing the electric bill is equivalent to reducing the on-grid energy consumption during one period. In this setup, the algorithm aims at switching-off (get into sleep mode) the highest possible number of BSs with low RE. This is done in two phases. The first phase considers BSs with zero allocated RE, members of the set B_{nr}. These BSs have higher priority to be switched-off since they are not capable of increasing their allocated RE and will always rely on the grid. They are sorted in increasing order based on their respective loads. Starting with the BS with lowest load as the first candidate, the process of switching-off is applied until there are no more candidates. The second phase considers the BSs in set B_r with energy depletion rates (EDRs) greater than 1, i.e. allocated RE is not sufficient. The EDR is the ratio of energy demand to allocated RE of the BS during the period, $EDR_{b,i} = \frac{D_{b,i}}{Ea_{b,i}}$. Switching-off is applied starting with the BS with the greatest EDR until there are no more candidates.

For the two previous phases, the process of switching-off is done by off-loading the traffic to the neighbour BSs. In case of lack of capacity in the neighbor BSs or unsatisfaction of any user, the algorithm skips to the next candidate BS.

4.4.2 Transmit power update

In many cases, it is not possible to switch-off a BS due to capacity constraints of neighboring BSs and/or QoS demand of user(s). However, it might be possible to contract the cell size to match the BS energy demand with the amount of allocated RE. In this process, the non switched-off BSs in set B_r, with EDRs greater than 1, are considered. Their transmitting powers are reduced simultaneously to avoid ping-pong effect and lower their power demand and thus decrease their EDRs. For each BS, we distinguish three cases. First, reducing the transmit power of a BS results in EDR less than or equal to 1. In this case, the BS will rely on RE and no on-grid energy will be consumed. Second, the EDR is decreased, but remains greater than 1. If the re-allocation policy is capable of matching the re-allocated RE with the demand, then no on-grid energy is consumed. In the previous cases, the BSs are no longer considered

Algorithm 1 Proposed electric bill reduction algorithm.

Inputs: storage level, price of on-grid energy $Price_i$, user distribution and quality requirements

Output: network configuration

Start-algorithm

Step 1: Decompose the BSs into two sets

- Define set B_r: BSs with available RE
- Define set B_{nr}: BSs without RE (zero RE and zero storage)

Step 2: **For** each BS in B_r:
Initiate $I_{b,i}$ as a percentage of stored energy

Step 3: Switching off BSs // see sub-Section 4.4.1

- Sort the BSs in set B_{nr} in increasing order based on their loads
- Switch-off all possible BSs of B_{nr}*
- Sort the BSs in set B_r in decreasing order depending on their Energy Depletion Rates (EDRs)
- Switch off all possible BSs of B_r

Step 4: transmit power update and RE re-allocation // see sub-Sections 4.4.2 and 4.4.3

while {on-grid energy is saved} **do**
Reduce the transmit power by one level of the non-switched BSs in B_r with EDRs greater than 1
If all users satisfied:
Apply RE re-allocation policy
else:
revert to previous configuration and go to **Step5**
end-if
calculate the saved on-grid energy
end-while

Step 5: Radio resource block scheme // see sub-Section 4.4.4, **For** each active BS:

- determine the number of active resource blocks*
- apply RE re-allocation policy for on-grid BSs

End-algorithm

* all users must be satisfied

in the next iteration of transmit power update. However, if the EDR is still greater than 1 and the re-allocation policy does not satisfy the demand, the BS is considered in the next iteration of transmit power update. The iterative approach combining the transmit power update and the re-allocation policy stops if no on-grid energy is saved or if there is at least one unsatisfied user.

4.4.3 Renewable energy re-allocation policy

A BS relies on RE if the allocated RE is equal or higher than the energy demand. Thus, BSs will try to increase their allocated energy to meet the demand. A re-allocation policy is applied depending on the grid energy unit price and the on-site storage level. Let $I_{b,i}$ and $D_{b,i}$ be the initial allocated RE and the energy demand of BS b at period i respectively. We quantize price and energy storage into three levels: low, medium and high. For each BS b, the re-allocated RE is expressed as follows:

$$Era_{b,i} = \begin{cases} D_{b,i}, & x = 1 \text{ and } Es_{b,i} \geq D_{b,i} \\ I_{b,i}, & \text{otherwise} \end{cases} \tag{4.24}$$

where x is in function of the price and storage level. $x = 1$ if the price is high, the level of the storage is high or the price and the level of the storage are medium. Re-allocating RE in the case of high price is intuitive to increase the reduction of the electric bill. In case of high level of stored energy, re-allocation aims at avoiding the energy wastage due to unavailability of storage capacity in the future. The case of medium price and level of battery is a compromise to avoid energy wastage and reduction of the electric bill in the same time.

4.4.4 Radio resource allocation scheme

Determining the number of active resources is often used in the context of energy saving. However, introducing RE in cellular networks provides a special case, where different cell sizes are obtained. The cell size is highly dependent on RE availability and allocation. Thus, different number of users would be served by each BS according to its cell size. We aim at reducing the number of excess active resources to decrease the energy consumption of the BS. To avoid time-consuming, complex allocation methods, we propose a heuristic algorithm that determines the number of active resource blocks proportional to the number of associated users by taking into account the cell size and traffic intensity. The number of active resource blocks for BS b in period i is determined as follows:

$$n_{b,i} = \lceil n_{b,max} \times min\{1, \lambda_i \times \mu \times S(P_{b,i}, P_{b,max})\}\rceil \quad (4.25)$$

where λ_i is the traffic intensity parameter that is the ratio of the traffic in period i to the maximum traffic, μ represents a correction parameter ($\mu > 1$) to ensure availability of active resource blocks for satisfying the users, S(.) is a function that calculates the ratio of the estimated cell area (with acceptable SINR due to the transmitted power $P_{T_{b,i}}$) to the maximum cell area (with acceptable SINR due to $P_{T_{b,max}}$). S(.) takes into consideration the path-loss, shadowing, noise figure and different characteristic of the BS and its antenna(s). $\lceil a \rceil$ denotes the smallest integer greater or equal to a.

For later use, EBR-RRA and EBR are denoted for the proposed algorithm for electric bill reduction with and without the RRA scheme (**Step 5**) respectively.

4.5 System model

We consider 25 macro BSs located on a 5x5 grid, with 2000 m inter-cell distance. Mobile users are uniformly distributed, with maximum number of users equal to 450. The traffic intensity estimation is based on [84]. We assume that the network has complete knowledge of users' positions. BSs operate with 2 GHz carrier frequency and 10 MHz bandwidth. We adopt cost 213 Walfisch-Ikegami for path loss [83] and consider the noise figure as 9 dB. Moreover, lognormal shadowing is considered with 8 dB standard deviation. All BSs are equipped with solar panels and a storage system. The price variation of on-grid energy is taken from [91]. Parameters' values and assumptions of the system are summarized in Table 4.1. Simulations are carried for a 24-hour scenario divided into 240 periods of 6 min duration. The chosen duration (6 min) verifies the following: 1) The change of RE generation is negligible (if it exist) during this duration, 2) This duration provides flexibility for the system to adjust its configuration with the variating conditions 3) The system has the same configuration during the period, which provides stability for a reasonable time. It should be noted that the results presented next are the average of many simulations done by varying the renewable energy generation pattern, on-grid energy price and users distribution.

4.5.1 Results and discussion

Strongest Signal First (SSF) is used as the reference user association algorithm for different results. We also compare our algorithm to the Cell Size Optimizing (CSO) algorithm presented in [56]. CSO is an iterative approach combining energy allocation/re-

Table 4.1: Parameters' values and assumptions.

Parameters	Values and assumptions
Number of BSs	25
Number of sectors in a BS	3
Number of periods p	240
Period T	6 min
Carrier frequency	$2GHz$
Bandwidth	10 MHz, FDD
Maximum transmitted power	43 dBm
Number of power levels	20
Inter-cell distance	2000 m
Number of resource blocks	50
Resource block bandwidth	180kHz
$SINR_{eff}$	1.2
BW_{eff}	0.83
Maximum number of users	450
User distribution	Uniform
User bit rate (R_{th})	360 Kb/s
Path loss	Cost 231 Walfisch-Ikegami [83]
Scheduler	Round Robin
Noise figure	9 dB
BS power model	EARTH [60]
P_{sleep}	75 $watt$
RE generation %	$20, 40, 60, 80$
Lognormal shadowing	standard deviation 8 dB

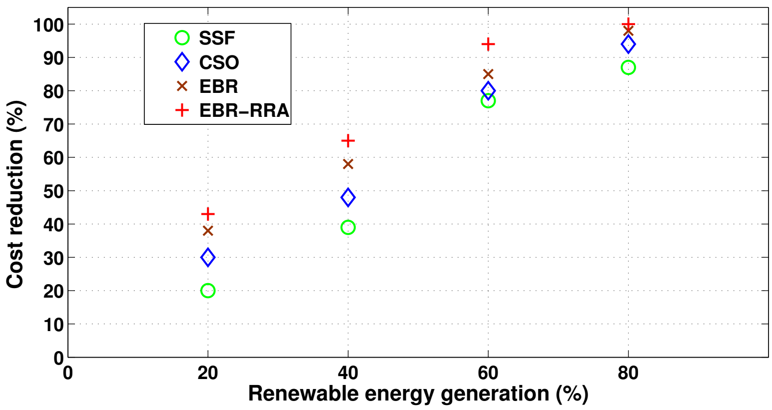

Figure 4.1: Cost reduction with respect to SSF according to RE generation.

allocation policy, which is based on the state of the storage, and a cell size adaptation algorithm. When the approach converges, a BSs switching-off mechanism is applied based on a pre-defined threshold of energy consumed per user.

In order to highlight the effect of cooperation between BSs, we use the same generation pattern and same amounts of energy used for powering a single BS to evaluate SPAEMA in Section 3.3.2. However, we consider small variations in the RE generation due to temporary conditions (clouds for example). In comparison with a single BS, the amount of generated energy represents lower percentage of average demand of a BS in a network. For example, an amount of RE that corresponds to 25% of energy demand of a single BS corresponds to 20% of the BS demand in case of network. This is due to the effect of interference and conditions considered in RE production. However, we see significant energy cost reduction of a network compared to a single BS. For example, when a single BS achieves 27% of cost reduction, the network was able to achieve 30%, 39% and 42% using CSO, EBR and EBR-RRA respectively. Similar conclusions are drawn for higher RE generations. This shows the significant impact of cooperation between BSs.

Figure 4.1 shows the cost reduction of SSF, CSO, EBR and EBR-RRA algorithms according to the generation of RE, which is presented as percentage of energy demand of the network in the reference case SSF. The network achieves the lowest cost reduction without any energy allocation policy or BS cooperation, case of SSF. On the other hand, EBR (without RRA) results in significant cost savings in comparison to CSO. Figure 4.2 shows that the energy demand reduction of the network is very close using CSO and EBR, which leads to the conclusion that the difference in the cost reduction is not due the energy reduction. The first explanation of the saving is the RE allocation policy of EBR that is based on the energy price and the state of the storage, while

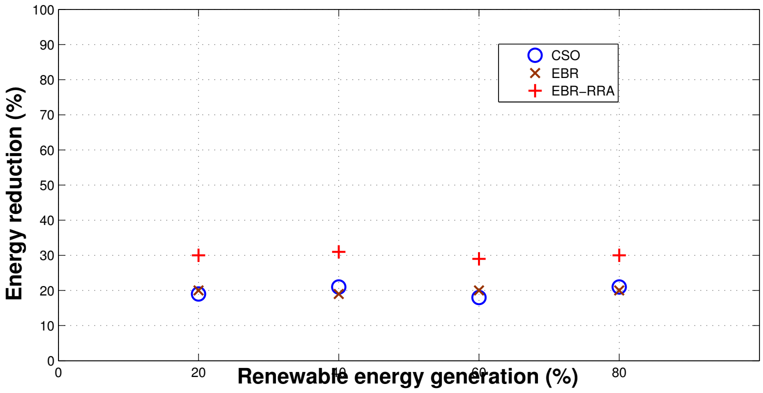

Figure 4.2: Network's energy demand reduction with respect to SSF according to RE generation.

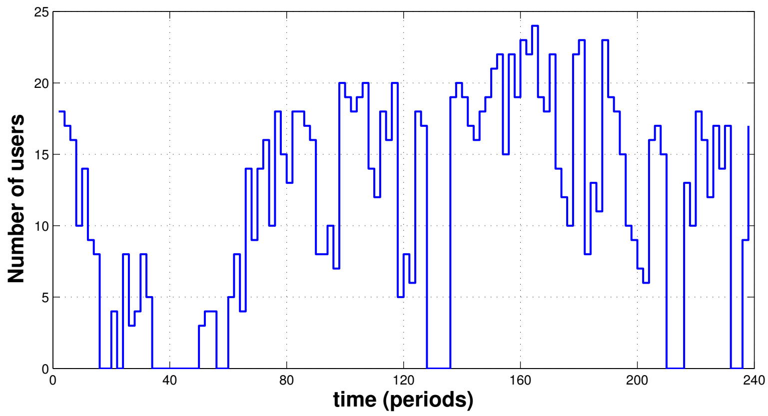

Figure 4.3: Number of associated users with a BS through a day.

CSO allocates RE depending only on the state of the battery. However, the margin of allocating RE becomes narrower for high RE generation (e.g. case of 60%). Yet, EBR still outperforms CSO in terms of cost reduction. Thus, we can conclude that the on-grid energy minimization in EBR is more effective than in CSO overall.

Figure 4.3 presents an example of the number of users associated with one of the BSs through a day using EBR-RRA. We can distinguish three cases: no-users, relatively low number and high number of users. The first case is due to the period of the day and/or the possibility of distributing the load to neighborhood BSs. The BS is switched into sleep-mode in this case. In the case of low number of users, RRA reduces the energy consumption by lowering the active radio resource blocks. Introducing RRA achieves higher cost saving with respect to the other algorithms as shown in Figure 4.1. This is due to its significant energy demand reduction shown in Figure 4.2. However, the

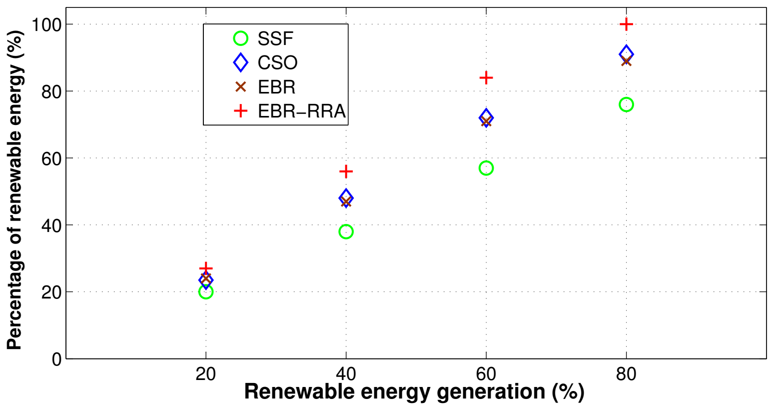

Figure 4.4: RE percentage of the total consumed energy according to the amount of generated RE.

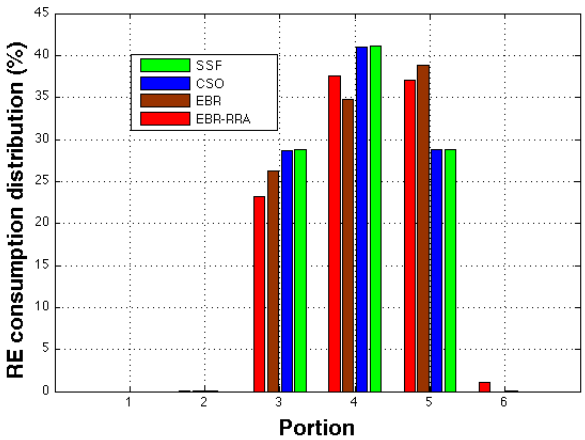

Figure 4.5: RE consumption distribution in different portions of a day for 40% of renewable energy generation.

gains in terms of energy reduction and cost reduction are not equal due to RRA. This illustrates once more that energy reduction and reducing the electric bill are correlated but not identical.

Figure 4.4 shows the RE percentage of the total energy demand. As the generated RE increases, the percentage of consumed RE increases. Analyzing Figure 4.2 and 4.4 shows that introducing RRA increases the percentage of consumed RE by decreasing the energy demand. This allows to increase the number of BSs relying on RE and decrease the energy consumption of on-grid BSs. We should note that only EBR-RRA achieves 100% cost reduction for RE sufficient for 80% of the network demand in its default configuration (SSF). Moreover, extra RE is produced in this case and can be

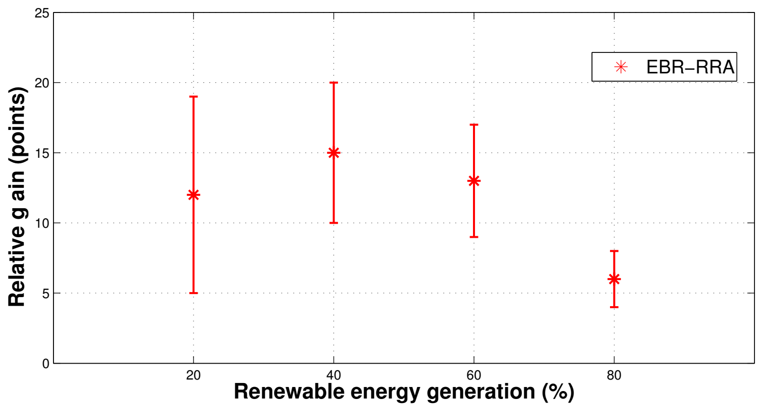

Figure 4.6: 95% Confidence interval of the relative gain of using EBR-RRA with respect to using CSO according RE generation.

sold to the grid. For higher generation of RE, CSO and EBR have almost the same effect on the cost reduction and on-grid consumption (converge to 100% reduction). However, EBR-RRA lowers the energy consumption and thus enables for higher profits by selling excess RE to the grid if possible.

Figure 4.5 shows the distribution of RE consumption used in different portions of the day (each portion corresponds to four hours) in case of 40% RE generation. The network does not consume RE in portion 1, 2 and 6 since they are during the night when energy storages are depleted. EBR and EBR-RRA consume less than SSF and CSO in portions 3 and 4. On the other hand, EBR and EBR-RRA consume more RE in portion 5. This is due to the price variation where the average price in portion 5 is higher than in portions 3 and 4.

Figure 4.6 shows the 95% confidence intervals of the gain of using EBR-RRA with respect to CSO. The results are consistent with the base study presented before. For example, the gain for 40% of RE generation ranges from 10 to 20 percentage points. The range of the gain is large for low RE generation, where it is highly dependent on the period of generation and the possibility of allocating RE in high price periods. Then, the range decreases, yet the gain is still significant, with the increase of RE generation. This emphasizes the efficiency of the proposed algorithm in different conditions of RE generation and users distribution.

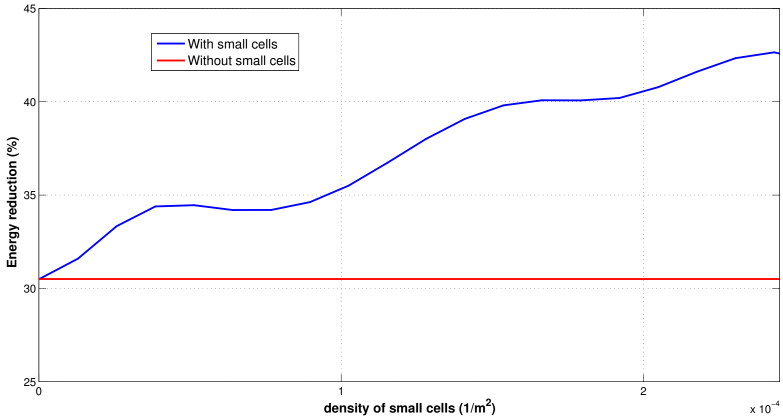

Figure 4.7: Energy demand reduction according to density of small cells.

4.6 Heterogeneous scenario

Although heterogeneous architectures were initially introduced as a solution for coverage and capacity extension, they are frequently used for enhancing the energy performance of the system. In particular, small cells with low energy demands are encouraged to be used in the context of RE powered cellular networks. For example powering a femto- BS needs less than $1m^2$ of solar panels as illustrated in [18].

Thus it is interesting to study the effect of adding small cells on the energy behaviour of cellular networks knowing that small cells can be purely powered by RE. With the same system model in Section 4.5 for Macro- cell, small cells are distributed according to independent homogeneous Poisson point process with density λ_s measured as number of BSs in $1m^2$. We consider that users receive interference only from Macro BSs and interference from small cells are neglected. Small cells does not go to sleep mode. However, it is possible to put them in sleep mode for reducing the energy consumption when they are not powered by RE. Users are associated as follows: the user associates with highest SINR received from a small cell. A user not able to be served by any small cell associates with a Macro cell. The configuration of Macro BSs follows the EBR-RRA algorithm presented before.

We variate the density of the small cells λ_s to study the energy reduction and the cost saving of the Macro- BSs. The results are for the case of RE generation equal to 20% of the macro- base stations total energy demand. Moreover, the energy demand of small cells is satisfied by RESs deployed at their sites. Simulations are repeated many times and the results we present next are the average value of these simulations.

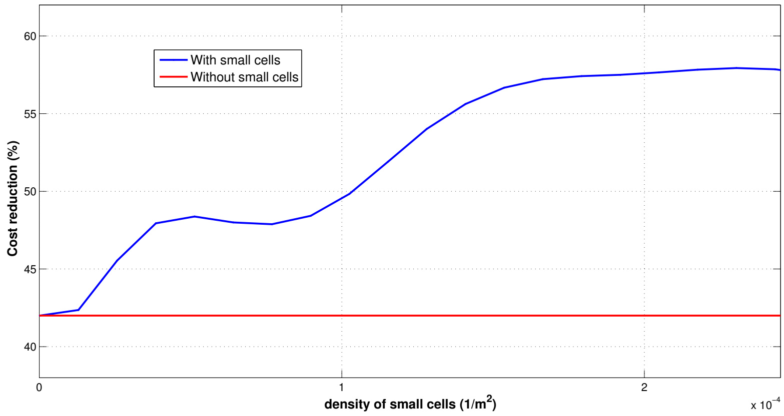

Figure 4.8: Cost reduction according to the density of small cells.

Figure 4.7 presents the energy reduction of using EBR-RRA with and without small cells according to the density of small cells. Results shows that adding small cells increases the energy reduction of the network. However, this reduction is not proportional to the density of small cells. When adding small cells, some users are offloaded from the macro- base stations. This leads to switching-off some of active macro- base stations. When adding small cells in small densities, some of low load macro- base stations offload users and go to sleep mode. These base stations could not be offloaded before in the case of no small cells. Increasing the density of small cells leads to more energy reduction until certain limit. The energy reduction remains at this limit even if we increase the density of small cells. This is because these small cells are not enough to switch-off more Macro cells. After additional increase of small cells, energy reductions starts to increase once again. This pattern is repeated as shown in Figure 4.7.

In Figure 4.8, the cost reduction of using EBR-RRA with and without small cells according to the density of small cells is presented. The figure shows that using small cell would lead to more than 57% of energy cost reduction. The cost reduction curve follows the energy reduction curve presented in Figure 4.7. Cost reduction increases with the increase of energy reduction. However, the energy cost reduction depends on the time of energy reduction as mentioned in Section 4.5.1. For example at high density of small cells, energy reduction increases while cost reduction is not significantly affected.

4.7 Conclusion

In this chapter, we have studied the problem of reducing the energy operational cost of a network of Macro- base stations. The problem is decomposed into 3 sub-problems: renewable energy allocation, energy consumption minimization and radio resource allocation. To address the problem, we proposed a new algorithm that adjusts the configuration of the network by allocating and re-allocating renewable energy, switching-off base stations, adjusting the transmitted power and determining the number of active resource blocks. Results show the effectiveness of cooperation between base stations and the possibility of significantly reducing the energy operational cost for small amount of renewable energy. Finally, we studied the effect of deploying RE powered small cells, where further cost reduction is achieved.

In the following chapter, we study the effect of base stations switching-off and renewable energy allocation in terms of on-grid energy saving and energy cost reduction for a real network layout of a major European mobile network operator. The specificity of the case reduces the complexity of the problem and impose the need for a new algorithm to operate the network.

CHAPTER 5 Renewable energy use in deployed cellular networks

5.1 Introduction

In the previous chapter we studied the problem of minimizing the energy operational cost of a network of macro base stations. However, the problem was generic and results were based on the simulation of the network behavior. In this chapter, we analyze the usage of renewable energy in a realistic environment. We evaluate the effect of renewable energy allocation and base stations switching-off in terms of on-grid energy saving and energy cost reduction based on real measurements of a major European mobile network operator.

In contrast to the problem studied in Chapter 4, we do not use transmitting power adjustment of base stations, since the operator considers it risky as it may have undesired effects on the interference level in the network. Thus, it is preferable to put base stations in sleep mode when the traffic is low, provided that the coverage of the network is ensured. In addition, the mobile operator provides an operational network optimization tool that finds the possible sets of base stations that can be switched together. In this case, the complexity of the problem considered in Chapter 4 is reduced.

We start by presenting the network layout. Then, we discuss the impact of sleep mode on the coverage of the network and analyse the influence of traffic on its energy consumption. We propose two algorithms based on two approaches: energy efficiency and cost reduction. Finally, we provide the results and observations about energy reduction and cost savings and analyze the usage of renewable energy in this environment.

This work was done in collaboration with our partners in Celtic Opera net-2 project.

5.2 Actual network scenario

We consider an actual network layout of a 4G LTE network belonging to a mobile network operator in a dense urban area of a big European city. Our considered scenario consists of 19 indoor BS sites (51 sectors), 10 MHz bandwidth operating at 2.6 GHz carrier frequency. Out of 19 sites, 15 sites are with 3 sectors each, 2 sites are with 2 sectors each and each of the remaining 2 sites consist of 1 sector only. The sites are numbered as $1, 2, \ldots, 19$.

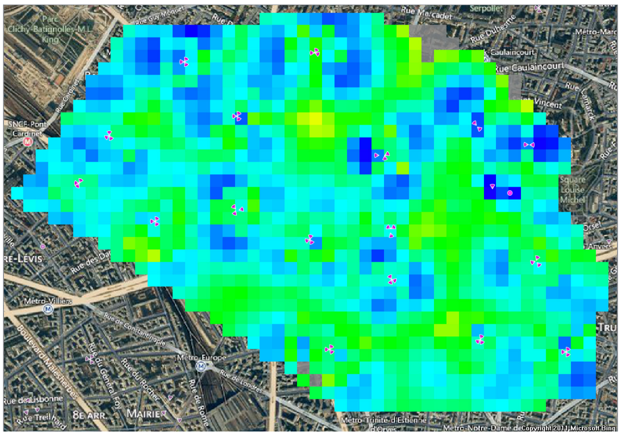

Figure 5.1: Coverage map when all 19 sites are active (areas whose color is close to blue have high throughputs while yellow areas have low throughputs).

Figure 5.1 shows the coverage map when all sites are active. Different colors on the map represent the QoS in terms of achievable user throughput for different radio conditions. A user located in blue regions achieves more throughput than that is in the green ones.

5.2.1 Coverage in dense urban areas

With the arrival of each new technology, the MNO deploys a number of sites with the objective to ensure coverage and capacity. While coverage is the limiting factor in rural areas, capacity is what matters in dense urban areas. Indeed, the system is over-provisioned so that the coverage of the different BSs overlaps with the aim of reusing spectral resources geographically in order to have more capacity. This over-provisioning impact is amplified in the case of 4G deployments as 3G sites may be reused irrespective of the real traffic, making the 4G sites highly under-loaded in the first deployment phases.

sites in sleep mode	sectors in sleep mode	coverage
0 (0%)	0 (0%)	97.13%
1 (5.26%)	3 (5.88%)	96.11%
4 (21.05%)	10 (19.60%)	95.74%
7 (36.84%)	16 (31.37%)	95.09%
8 (42.11%)	19 (37.25%)	89.81%

Table 5.1: Coverage according to the percentage of sites and sectors put in sleep mode.

Our focus is to obtain the over-dimensioning ratio by identifying the maximum number of sites that can be switched off without compromising coverage. We make use of an operational network optimization tool. The optimization process uses an algorithm based on a combinatorial optimization model where the set of feasible solutions is discrete and the goal is to find the best possible solution. The optimization engine takes coverage criteria as an objective constraint to satisfy.

The coverage criteria is set to be equal or greater than 95%. First, we keep all sites of our considered network active and observe 97.13% coverage. Staring from 1, we go on increasing the number of sites in sleep mode until coverage falls below the set threshold of 95%. We find that 7 out of 19 BS sites (36.84% of total sites) or 16 out of 51 sectors (31.37% of all sectors) can be put in sleep mode by respecting the coverage constraint. Therefore, if we further increase the number (%) of sites to be put in sleep mode, then we notice that coverage constraint is violated. The number (percentage) of sites in sleep mode and the corresponding coverage values in % are given in Table 5.1.

Figure 5.2 shows the coverage maps providing more than 95% coverage when maximum percentage (i.e. 36.84%) of sites can be put in sleep mode. We observe that left over uncovered spots by deactivated sites are covered by their active neighbors. If we have a close look at center left side of both maps (Figures 5.1 and 5.2), we find that the color changes from blue (more throughput) to green (less throughput) when deactivating the BSs, which means that throughput of users decreases to some extent.

5.2.2 Capacity of the base station site

Assume that we have a given number of users, then we have equal and random division of resources (i.e, time slots and Resource Blocks in HSDPA and LTE respectively)

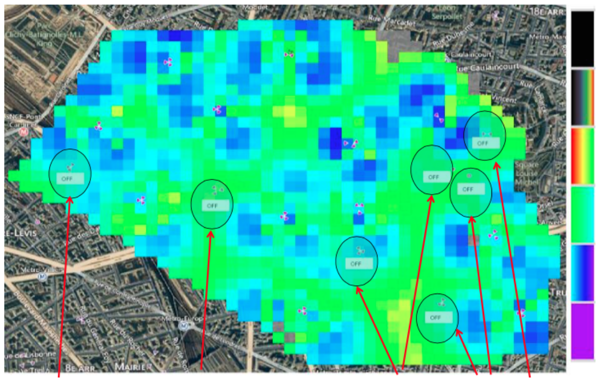

Figure 5.2: Coverage map when all 7 sites are OFF.

among users. A user (being alone in the cell) close to the BS will possess different bit rate as compared to the scenario when he is far from the BS. The throughput of a user will decrease with the increase of his distance from the BS. In realistic settings as illustrated in Figures 5.1 and 5.2, large peak rate throughput variations can be observed and each cell of the network can be divided into regions with comparable radio conditions and hence a common achievable throughput. We observe M_i different regions of radio conditions belonging to the BS site i. p_{ij} is the proportion of users of cell i that are situated in region $j \in [1, M_i]$, and have thus throughput C_{ij}.

The amount of traffic volume offered to the BS site i per unit time is $V_i = \lambda F$, where we consider that radio conditions of users remain same during the communication with the assumption that connection demands arrive to the cell according to a Poisson process of intensity λ connections per second. Moreover, each connection brings an average amount of traffic equal to F mega bits and thus the offered traffic is in Mbps. Then, the normalized traffic load produced by users belonging to radio condition j of site i is given by

$$\rho_{ij} = p_{ij} \times \frac{V_i}{C_{ij}} \tag{5.1}$$

The overall normalized load on BS site i is given by [92]:

$$\overline{\rho}_i = \frac{V_i}{C_i} \tag{5.2}$$

whereas C_i is the capacity of the BS site i and corresponds to harmonic mean of achievable throughput observed over the BS site area and is given by [92]:

$$C_i = (\sum_{j=1}^{M} \frac{p_{ij}}{C_{ij}})^{-1} \tag{5.3}$$

The harmonic mean gives more weight to cell edge users (positions with lower rates). With low mobility, a user does not change radio conditions during a typical call and

Parameter	Description
N_i^{sec}	number of sectors of site i
P_0	minimum non-zero transmitted power at no load
P_{max}	maximum transmitted power at full load
P_{sleep}	power in sleep mode
Δ_p	slope of load-dependent power consumption
$\overline{\rho}_i$	variable (from 0 to 1)

Table 5.2: Parameter description.

hence accumulates at cell edges resulting in capacity regarded as harmonic mean of achievable throughput.

5.2.3 Influence of traffic variation on energy consumption

In this section, we aim at analyzing the power demand of a BS based on its traffic. We consider the EARTH power model presented in Section 2.4.1. We use its linear approximation that is given by:

$$P_i = \begin{cases} N_i^{sec}\left(P_0 + \Delta_p * P_{out}\right), & 0 < P_{out} \leq P_{max}, \\ N_i^{sec} P_{sleep} & P_{out} = 0. \end{cases} \tag{5.4}$$

whereas P_i is the power of the base station, N_i^{sec} is the number of sectors of the base station, $P_{out} = P_{max} * \overline{\rho}_i$ is the transmitted power, P_0 is the power consumption at the minimum non-zero transmitted power, Δ_p is the slope of load-dependent power consumption and P_{sleep} represents the power consumption in sleep mode. The various parameters of the power model for a macro BS site i depending on number of sectors are presented in Table 5.2.

Based on the presented power model we present in Figure 5.3 the real traffic load variation and the corresponding power consumption for a day of a base station consisting of 3 sectors, 10 MHz bandwidth. In this figure, the power is normalized with respect to the power demand at full load, and the traffic load is calculated as the ratio between measured traffic and the capacity presented in Equation 5.3. We notice that irrespective of the variation in traffic volume, energy consumption does not follow the similar variations. Moreover, the BS still consumes a large amount of power when the traffic is low, which means that the energy efficiency of the BS site is very low during low traffic periods. Here, by energy efficiency, we denote the amount of information carried for every unit of energy. Thus, dynamic adaptation to traffic variations is must for a network in order to exhibit efficient use of power resources.

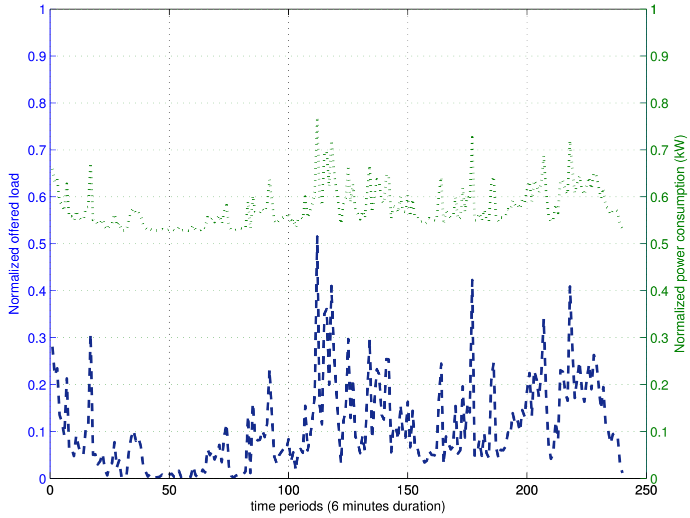

Figure 5.3: Normalized power consumption (with respect to power at full load) and offered traffic for a real macro BS site.

5.3 Energy cost reduction problem statement

5.3.1 Energy efficient approach

The over-provisioning and the low energy-efficiency of the considered network presented in Sections 5.2.1 and 5.2.3 promote the need for an energy efficient operation of the BSs. However, coverage and QoS constraints should be respected. For a period T the problem of minimizing the energy consumption (or power demand) of the considered network can be expressed as:

$$min(\sum_{i=1}^{i=19} P_i \times T) \tag{5.5}$$

$$subject\ to:$$

$$\Delta_{QoS} < th_{QoS} \tag{5.6}$$

$$Cov \geq th_{cov} \tag{5.7}$$

where P_i is the power demand of base station i. Δ_{QoS} is the degradation of quality of service, which should be less than a threshold th_{QoS}. Cov is the coverage of all base stations which should be more than a minimum value th_{cov}. In addition, we consider constraints related to system design (as in Equations 4.3 and 4.4) when applying the algorithms presented in Section 5.4.

5.3.2 Energy cost reduction approach

Considering that the mobile network is powered by RESs and operates in the Smart Grid environment, where the price of on-grid energy variates, the problem shifts to minimizing the energy operational cost. In Section 4.2, we presented a generic problem formulation for reducing the energy operational cost for a network of base stations. The formulated problem is still applied in this case. However, the considerations of the mobile operator and his optimization tool reduce the complexity of the problem. We are able to decompose the problem into two phases, where the first phase can be done in advance (off-line) and the second phase is applied in real-time as presented in the following section.

5.4 Proposed algorithms

In this section, we present our proposed algorithms for energy efficiency and energy cost reduction. Energy efficiency switch-off algorithm aims at minimizing the energy consumption of the network, while energy cost reduction algorithm aims at minimizing the cost of on-grid energy by better utilization of RE.

Based on the coverage analysis in Section 5.2.1, we can identify the BSs that are capable of switching-off together without violating the coverage threshold. This step is done off-line, where the MNO identifies the sites of its network that can be switched-off without coverage loss. We denote S_o as the o^{th} set of BSs that can switch together and its respective complement as S_o^*, the set containing all the BSs except those in S_o.

A BS site that belongs to S_o^* can accommodate, in addition to its own traffic, the traffic offered by neighboring BS sites belonging to S_o (may vary from 0 to maximum number of sites in S_o). Similarly, a BS site belonging to S_o can transfer its traffic to 1 or more active BS sites of S_o^*. A BS site belonging to S_o^* is allowed to accept traffic only if its total normalized load does not exceed a certain threshold. Here, total normalized load is the ratio of the sum of all offered traffic loads (i.e., own load of site i, already accepted load from any site(s) of S_o and load to be accommodated as a result of current request) to the capacity after optimization which is denoted by C_i'.

In practice, we use the information obtained from coverage maps, and identify for each leftover spot by site(s) going in sleep mode the BS site(s) that cover(s) those spots. Thus, we obtain % of load transfer information among BS sites as given by Figure 5.4. Figure 5.4 presents an example of load transfer between BSs when sites 6, 8, 11, 14, 15, 16 and 18 are willing to go to sleep mode. Each of the curves in the figure

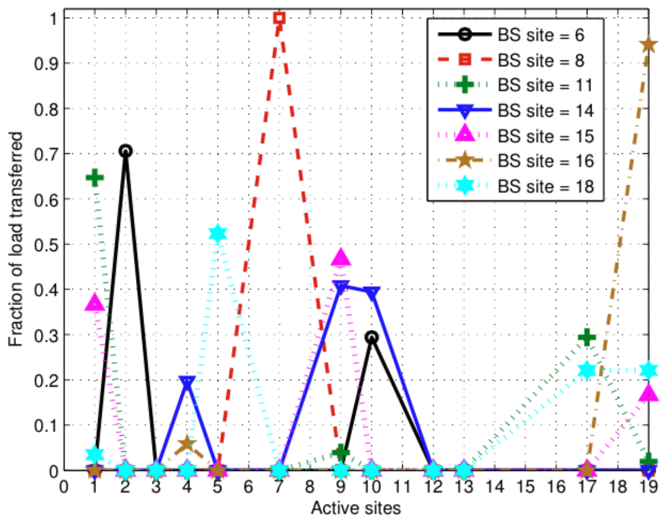

Figure 5.4: Load transfer information among BS sites.

represents one of theses sites, while the sites on x-axis are the sites that accommodate fraction of the loads (y-axis).

A BS site k can switches-off if its active neighbors can accommodate all its traffic while respecting their normalized load constraint. Let α_{ik} be the fraction of traffic volume which could be transferred to site i from its neighboring site k, which wants to go in sleep mode. Site i can accommodate traffic of its neighbors only if its normalized load $\overline{\rho}_i'(T)$ during a time period T does not exceed a certain threshold $\overline{\rho}_{th}$ on normalized load, which is given by:

$$\overline{\rho}_i'(T) = \frac{V_i(T) + \alpha_{ik} V_k(T) + \sum_{k' \neq k} \alpha_{ik'} V_{k'}(T)}{\overline{C}_i'} \leq \overline{\rho}_{th} \tag{5.8}$$

where $\sum_{k' \neq k}$ captures the fact that site i might have some load from sites of S_o other than that of site k. Site k can decide to go in sleep mode only if all its surrounding active neighbors can respect their normalized load threshold. Moreover, $\sum_i \alpha_{ik} = 1$ and $\sum_k \alpha_{ik} \geq 0$, the former expression says that traffic of site k could be completely shifted to all its active neighbor(s) i (site k could have one or more active neighbors which share its traffic), while the latter tells that site i could accommodate traffic partially or completely of one or more sites in sleep mode or even from non.

We consider that the day is divided into periods. In the case of energy cost reduction approach, the decision of using RE by each site follows the algorithm SPAEMA presented in Section 3.3.2 and is done at the beginning of each period. Then, the set of base station (to be deactivated) S_o^c is chosen such that its complement has the greatest number of BSs with allocated RE. This will increase the probability of switching-off

Algorithm 2 cost minimization switching-off algorithm

off-line step: // done only once

- Identify possible sets of BSs that can be switched-off together without violating the coverage constraint

on-line step: // done at beginning of each period

- For each BS
  - allocate RE using SPAEMA
- Choose the set of candidate BSs S_o^c based on RE allocation (details in Section 5.4).
- Set the status of all BS sites as ON
- Initialize list of sites in sleep mode during current period s to $\emptyset$
- For each site k belonging to S_o^c, we verify one by one
  - For each active neighboring site j of site k
    - Calculate the total normalized load
  - If the total normalized load of all active neighbors of k is less than the threshold $\overline{\rho}_{th}$
    - off-load the traffic of site k to its active neighbors
    - Add site k to the list s
    - Set the status of site k as OFF

BSs relying on the grid. The Energy cost reduction algorithm is presented in Algorithm 2. By removing the allocation process and choosing the candidate set S_o^c to achieve the highest energy saving, the algorithm describes the energy efficiency approach.

5.5 Discussion and results

The results, achieved through simulations, presented in this section are based on sites of real network and real traffic data traces from an European MNO. We consider an actual daily traffic profile divided in periods of 6 minutes each. The original data was in number of bytes per 6 minutes and the same was modified in Mbps. Our considered network scenario consists of 19 indoor BS sites serving macro cells. Moreover, it is important to mention that each sector has unique actual traffic profile. However, we have considered total traffic of the BS by accumulating the individual traffic volume of all sectors belonging to the same site. Among the 19 sites, several sets of possible combination of BSs that can switch together can be found such as S_1 and S_2 (S_1: 6,8,11,14,15,16 and 18 and S_2: 5,6,8,9,11,15 and 16). S_1 and S_2 represent the sets with maximum number of BSs capable of switching-off together (7 BSs). However, we notice that some base stations are not capable of being switched-off in any combination due to their critical location and coverage constraint. Note that S_1 is chosen in case of energy efficient approach as it is capable of achieving the highest energy reduction.

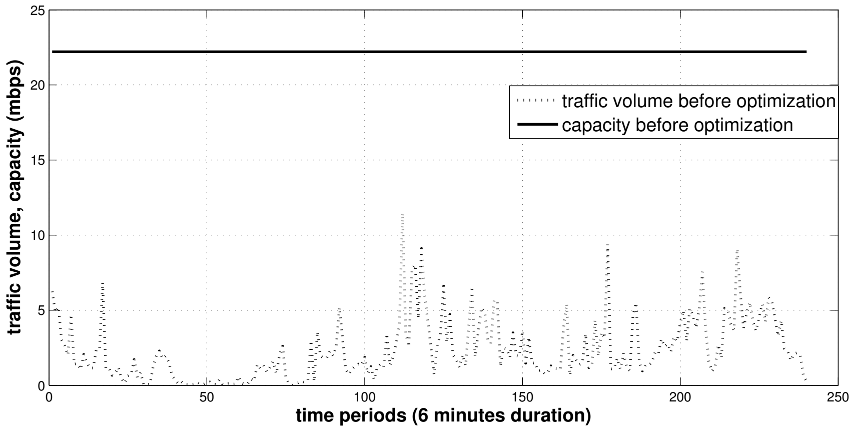

Figure 5.5: Offered traffic volume on a site which wants to go in sleep mode (site 18)

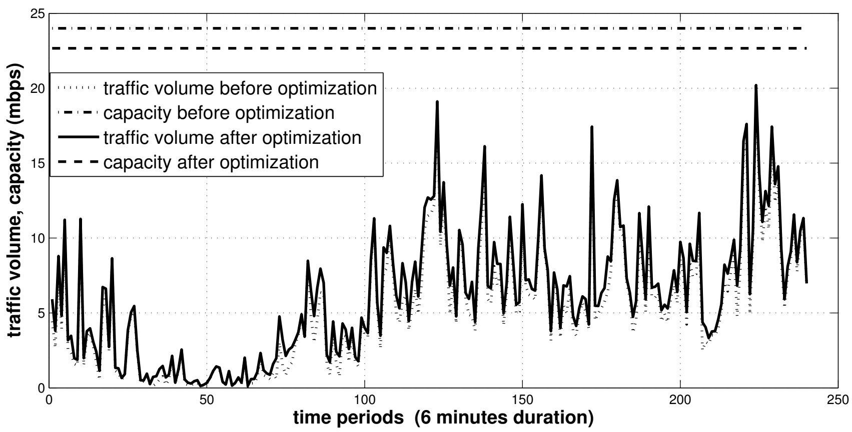

Figure 5.6: Total offered traffic volume on active site (site 19) before and after load sharing from site in Figure 5.5

After switching-off some BSs, we observe capacity change (increase or decrease) of some BSs. The decrease of capacity is due to coverage expand of the site and the increase is due to interference reduction (due to BSs switching-off). Figures 5.5 and

Table 5.3: Required Power values (in Watts) for any macro BS site with 1,2 or 3 sectors [60].

Mode	Power needed (in Watts)		
	$N_i^{sec} = 3$	$N_i^{sec} = 2$	$N_i^{sec} = 1$
Full load P_0	1350	900	450
Active, no load	712	474.67	237.33
Sleep mode (P_{sleep})	72	48	24

Table 5.4: Site configurations.

Parameter	Value
Antenna height	Variable
Propagation model	Hata model
Required Performance KPI	Coverage average user throughput
N^{sec}	Varies from 1 to 3
P_{max}	40 Watts
Load threshold	0.60
Δ_p	5.2
Generated RE	65 KWh

5.6 present the real traffic data and capacity (both in Mbps) of site 18 and site 19 before and after load transfer. We can notice that traffic load of site 18 is low during many periods of the day while site 19 does not possess heavy offered traffic and can easily accommodate transferred traffic from site 18. The same is true for other active neighbors of site 18 (similar type of figures).

Simulations parameters are based on Table 5.3 and Table 5.4. The results are shown for different algorithm variants to highlight the effect of each technique (RE allocation and switching-off BSs). For the different variants, the performance of the network is evaluated in terms of on-grid energy saving and cost reduction. Different on-grid price variations and renewable energy generation patterns are considered. The intermittency of renewable sources is taken into consideration, where we consider small variations in the production due to temporary conditions (clouds for example). The system does not have previous knowledge of the energy generation. The results are normalized with a reference case corresponding to the performance of the network without RE and working with default configuration, i.e. no switching-off. The variants are as follow:

- Variant A: no RE, efficiency switch-off.
- Variant B: RE is used, no switch-off.
- Variant C: RE is used, efficiency switching-off.
- Variant D: RE is used, cost reduction switching-off.

The synthesis and results of different variants are presented in Table 5.5 and are analyzed as follows:

Table 5.5: Saved on-grid energy and cost reduction for different algorithm variants

Algorithm	Switch-off criteria	RE	Energy reduction	Saved grid energy	Lost RE	Cost reduction
Variant A	Efficiency	_	18.69%	18.69%	_	17.1%
Variant B1	_	Traditional	_	19.6%	2%	17.9%
Variant B2	_	SPAEMA	_	19.3%	3.1	27%
Variant C1	Efficiency	Traditional	18.69%	38.1%	2.8%	40.2%
Variant C2	Efficiency	SPAEMA	18.69	37.7%	4.2%	43%
Case D	Cost	SPAEMA	17.9%	36.8%	5.5%	51%

Variant A This variant reflects the performance of the network when energy efficiency is adopted and RE is not used. In each period, BSs are switched-off to achieve highest energy savings such that the coverage and QoS constraints are respected. Coverage constraint can be ensured by the off-line step. However, QoS depends on the traffic intensity and the chosen load transfer threshold $\overline{\rho}_{th}$. Figure 5.7 presents the average power savings (%) and QoS reduction (%) according to the threshold value of normalized offered load on active sites $\overline{\rho}_{th}$. Increasing the threshold leads to the increase of the power saving but also increase in the QoS of degradation. When $\overline{\rho}_{th} = 0.6$, 18.9% of average power savings is achieved with less than 8 % of QoS reduction.

Figure 5.8 shows the total power demand of the network with sleep mode, without sleep mode, no load and full load (in case of $\overline{\rho}_{th} = 0.6$). By comparing the power demand with and without energy efficiency sleep mode, we calculate the power savings over 24 hour periods and present them in Figure 5.9 . We observe significant daily

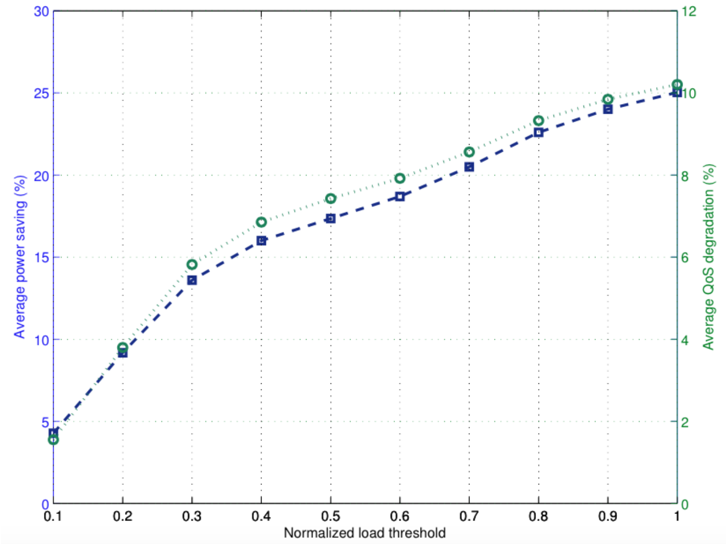

Figure 5.7: Average QoS and power saving according to the chosen value of $\overline{\rho}_{th}$.

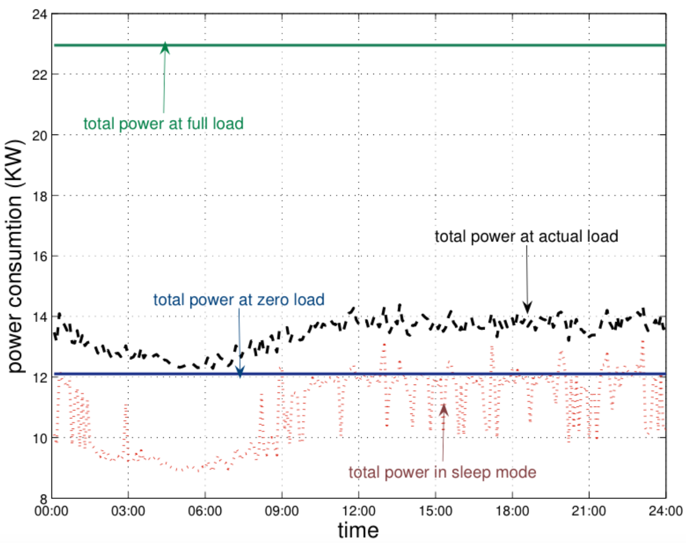

Figure 5.8: Overall power consumption with sleep mode, without sleep mode, no load and full load over 24 hours.

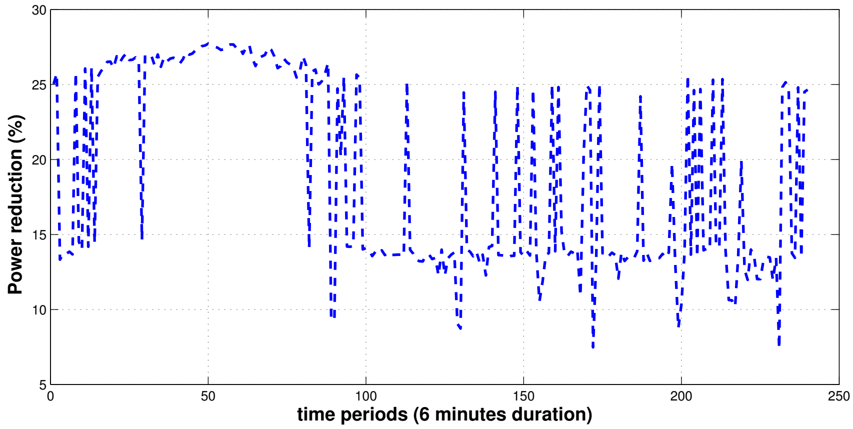

Figure 5.9: Overall percentage of power savings over 24 hours

average power savings of 18.96% (from 7.38% to 27.72%). Concerning the cost, we obtain 17.1% of on-grid energy cost reduction. One can easily notice that the percentage of cost reduction is less as compared to percentage energy savings. This is explained by the high correlation between high on-grid energy-price periods and high-traffic load periods, which prevents sites from switching-off.

Analysis of RE usage In order to analyze the possible usage of RE in the context of energy efficiency, we study the new energy demands of different base stations after switching-off. Table 5.6 shows the energy demand (kWh) before and after efficiency switch-off for all the sites of the network in a day.

We distinguish three types of base stations. Type 1 base stations, which do not go into sleep mode, have slight increase in energy demand due to traffic received from other BSs. Their energy demand is important (e.g. BS 19 has a demand of 20.8 kWh per day), and thus they need significant area (and investment cost) for deploying solar panels to satisfy the total demand. This is probably not possible due to site limitation in Urban areas. Base stations of Type 2 are rarely ON (active in few periods). Their energy demands are significantly decreased to small values (e.g BS 16 has a new energy demand of 0.8 kWh). In Type 3, BSs have significant decrease in their demands. Yet, their demands is still considerable (e.g. BS 15 has a new energy demand of 3.5 kWh). Based on this classification, we recommend the following:

- For Type 1, we recommend to use RESs taking into account price variation. Unlike many studies that aim at sizing RESs to obtain zero-grid energy, we recommend sizing RESs based on the energy demand within the high-price periods. This allows

Table 5.6: Energy demand (kWh) before and after efficiency switch-off, generated RE (kWh) and storage size (kWh) of each site of the network.

Site	Energy demand before switch-off (kWh)	Energy demand after switch-off (kWh)	Generated RE (kWh/day)	Storage size (kWh)
1	25.096	25.293	4	2
2	18.879	19.575	4	2
3	19.7	19.7	4	2
4	18.682	18.802	4	2
5	18.435	18.707	4	2
6	18.258	2.061	2	1
7	12.907	13.292	4	2
8	11.594	1.597	1.5	1
9	18.867	19.184	4	2
10	18.314	19.165	4	2
11	18.741	11.479	4	2
12	17.634	17.634	4	2
13	17.452	17.452	4	2
14	17.9	1.869	1.8	1
15	5.771	3.529	3.6	2
16	5.712	0.832	0	0
17	18.874	19.2	4	2
18	18.679	11.396	4	2
19	20.474	20.838	4	2
Total	321.969	261.605	64.9	33

avoiding high investment cost of both renewable sources and storage. However, it must be accompanied with an effective RE allocation algorithm to ensure using RE at the right time.

- For Type 2, it is recommended not to equip it with renewable sources, unless energy sharing/selling is possible, which is not our case.
- We found that Type 3 base stations are active more often during the high price durations. Thus, we recommend to equip them with renewable sources that can satisfy their energy demand, if the site's area allows such deployment.

- The size of energy storage at each site depends on the size and generation of RESs and the energy demands during high-price periods.

In the following algorithm variants, we consider the usage of RE. For each site, we consider a total amount of generated RE in one day considering special conditions at each site (such as clouds). This amount of energy varies between sites, where we follow the mentioned recommendations assuming that the maximum RE generated in one day by each site comes to be 4 kWh. This assumption is adopted to take into account the limitation of available site area. For different sites, we assume that each of them is equipped with an energy storage with 90% efficiency. The storage is capable of storing half of the total generated RE produced by the local renewable sources (maximum 2 kWh storage). Table 5.6 shows the generated RE (kWh) in a day and storage size (kWh) of different sites. The total amount of RE generated by all sites is 65 kWh, which is 20% of the total network demand without any switching-off.

Variant B In this variant, we study the effect of RE allocation without switching-off. We consider the basic use (traditional greed allocation) and the intelligent allocation policy SPAEMA of RE, which is the one presented in Section 3.3.2. In traditional use, BSs consume RE when it is available. Extra energy is stored in case of availability of a storage. On the other hand, the storage is used to compensate the energy demand when RE generation is not sufficient. Otherwise, grid energy is used. In both approaches, the amount of saved on-grid energy is equal to the generated RE subtracted from the loss due to efficiency of the storage. However, the second approach tends more to store energy, which will cause more loss. The cost reduction of the traditional approach (17.9%) is less than the percentage of saved on-grid energy (19.6%). This is not due to the loss due to storage's efficiency, as we see that intelligent RE allocation causes more loss (3.1% vs 2%) but also more cost reduction (27% vs 17.9%). The cost reduction due to renewable energy is highly dependent on the periods of RE generation and consumption.

Variant C In this case, we analyze the usage of RE in efficiency-based environment. BSs are switched-off to gain maximum energy reduction. Using RE with SPAEMA and traditional RE allocation causes 37.7 % and 38.1 % reduction of on-grid energy respectively as well as 43 % and 40.2 % of cost reduction respectively. In the case of using RE with traditional allocation (traditional), switching-off BS decreases RE consumption at low price periods and allows storing them for high price periods, and this explains the decrease in the effect of intelligent energy allocation between the cases with and without efficiency switching-off.

Variant D In this case, we identify the possible saving in the network by using the cost minimization switch-off algorithm. The percentage of saved on-grid energy (36.8%) is less than in efficiency case (37.7%). This is because RE is more-likely to be stored. Storing would be in case of low price and case of deactivated BSs. In other words, we have higher probability of storing RE to be consumed within high prices. This will increase the loss in RE but cause a significant reduction in the electric bill (energy operational cost). With RE sources that can produce only 20% of the total energy demand of the network, we can achieve 51% of electric bill reduction. This can be essential in studying the economic feasibility of using renewable energy sources, since limited investment is required but significant percentage of electric bill reduction is achieved.

5.6 Conclusion

In this chapter, we studied the minimization of energy operational cost of a real network of base stations. The coverage redundancy provided by overlapped base stations allows switching some of them to reduce energy consumption. After analyzing the coverage and capacity of the network, we presented two switch-off algorithms that aim at reducing the energy consumption and energy cost respectively. We found that it is possible to decrease up of to 51% of the electric bill by using renewable energy sources that produce only 20% of the network demand. These results encourage the idea of advance sizing of renewable energy sources and storage based on the network possible configurations (activation/ deactivation of base stations), renewable energy generation and price variation.

In the following chapter, we go a step further in studying the bahavior of base stations in the Smart Grid environment. In contrast to all our previous studies that consider the concerns of the mobile network operators, Chapter 6 presents our proposed architecture to facilitate the interaction between base stations and the Smart Grid. The base stations do not only aim at reducing their energy operational cost but also provide the grid with ancillary services.

CHAPTER 6

The Smart Grid and future cellular networks

6.1 Introduction

In the previous chapters, we considered the problem of minimizing the energy operational cost considering real time price of on-grid energy. In this chapter we study a new energy behavior of cellular base stations powered by renewable energy and the Smart Grid. We start by presenting the main characteristic of the Smart Grid. Then, we explain the evolution of the energy management concept due to powering base stations with renewable energy and considering the Smart Grid. Furthermore, we explain the mutual views between the Smart Grid and the Mobile networks and propose a new integration architecture that facilitates the interaction between them.

As an application of the integration architecture, we consider the case where the base stations provide ancillary services to the Smart Grid. We explain the Smart Grid environment in this case, and present the involved entities and the message exchange protocol between them. After formulating the problem as minimizing the energy operational cost of a base station, we propose a heuristic algorithm that exploits the concept of delay tolerant users and manages the generated renewable energy and energy storage to answer the grid requests.

6.2 What is the Smart Grid?

The Smart Grid is an evolution of the power grid [20], based on the integration of bidirectional communications to all parts of the grid. It is in essence an economical way to improve the efficiency of the grid, increase its capacity, improve the awareness of the grid (real-time and historical), allow for new services and new technologies to be integrated, for a fraction of the cost of the traditional methods.

The evolution in the main domains of the grid includes but is not limited to:

- Generation
  - Improve demand matching
  - Bulk distributed energy generation
- Distribution and Transmission
  - Integrate Electrical Vehicles
  - Integrate Distributed Energy Resources
  - Improve efficiency
  - Faster problem recovery
- Consumers
  - Demand reduction
  - Improve efficiency
  - Change consumption habits

The SG incarnates improvement in several aspects of the power grid, which includes both the technical ones, as well as in terms of services, business practices, legal issues and regulations. For example, instead of having few large power generators to supply many customers, the SG integrates distributed energy sources and efficiently delivers the power to the customers. Figure 6.1 shows the architecture of the traditional power grid. The energy is generated by central generators and then transported through the transmission and distribution systems to the load. The evolution of energy flows in the SG is shown in Figure 6.2, where bulk RE generation and energy storages are integrated at the generation level. At the distribution level, the SG introduces new appliances, such as electric vehicles, and integrates distributed RESs. The latter creates a new entity: the *Energy Prosumer*, which is is a combination of energy provider, where local RE is generated, and consumer of energy. A home or a BS with local RESs are some of the examples of a prosumer.

In case of failure or high variation in demand or supply, the SG can quickly responds to the events and automatically reacts to achieve fast recovery. This is due to its dynamic architecture that integrates smart infrastructure, management and protection systems. The infrastructure system includes the energy information and communication infrastructures. Advanced management and control services are provided by the

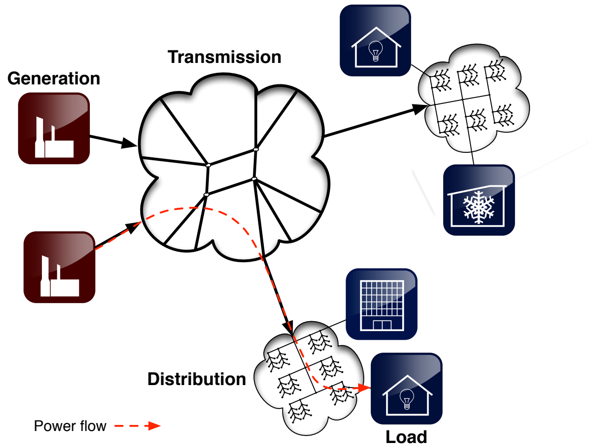

Figure 6.1: Power Grid architecture.

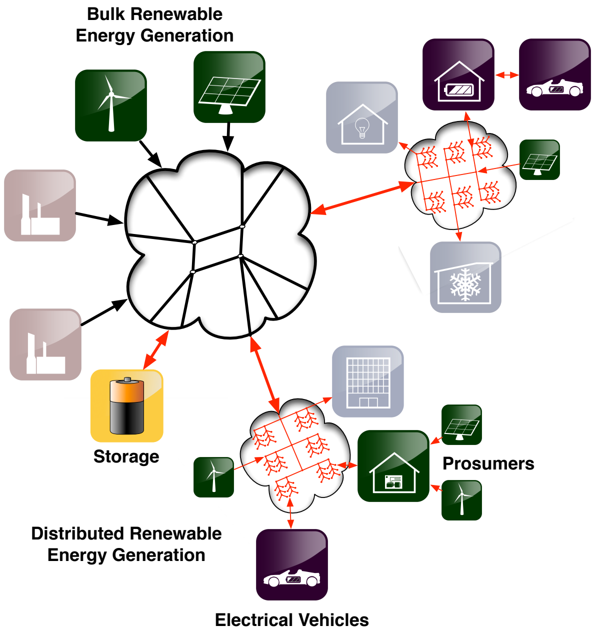

Figure 6.2: Smart Grid architecture.

management system. Moreover, the SG has a protection system that provides reliability and failure protection. For more information, see the exhaustive survey of Fang et al. in [20].

The development of economical aspects and regulations of the SG motivates the customers to be more involved. Customers are concerned with the price of electricity based on the adopted tariff system, which contributes to the profit of both the customer and the grid. On one hand, customers are interested in reducing their electric bill (and carbon foot-print). On the other hand, the price of electricity depends on the load, which will eventually contribute to decreasing the peak consumption. In this context, demand side management is a well known strategy that allows the consumers to adapt their consumption to the conditions of the grid [81].

Demand side management aims at guiding the customers to consume less energy during high consumption hours (peak hours) or shifting their consumption (to off-peak periods). Two strategies are open, direct-load control and demand-response. Using direct-load control, the SG controls the energy consumption of the devices. In the case of demand-response strategy, the grid sends a demand for the customer, who takes the decision. Choosing the strategy depends on several conditions including the type of customer and his criticality.

6.3 Energy management concept

The mobile network industry is a major energy consumer accounting for 13 billion dollar market [15] consisting of thousands different devices spread out geographically. The significant energy demand of mobile networks combined with the recent equipping of BSs with RESs and energy storage promote mobile networks operators to be one of the important players on the energy market. This motivates the definition of common policies between MNOs and the SG to increase their mutual benefits, and introduces a new concept *Grid-Aware Greening for Mobile Networks*.

The evolution of energy management concepts due to introducing renewable energy sources and considering the SG environment in the context of mobile networks is presented in Figure 6.3. The concepts are consistent with each other, as it is easier to power a mobile network with renewable energy, *Energy Sustainability*, if it has lower energy footprint, *Energy Efficiency*, to start with. Moreover, the state of the SG, such as pollution level or electricity price, is important in defining the utilization of renewable energy. Consequently, MNOs are not only concerned with decreasing the energy

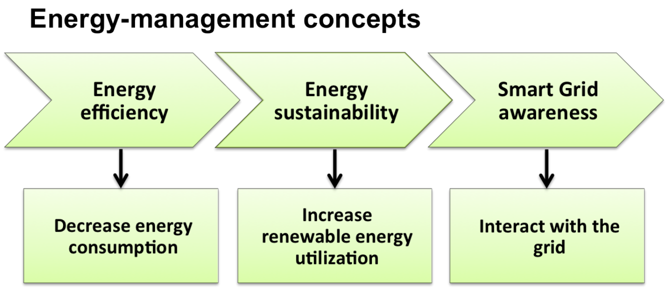

Figure 6.3: Evolution of energy management concepts in the context of mobile networks.

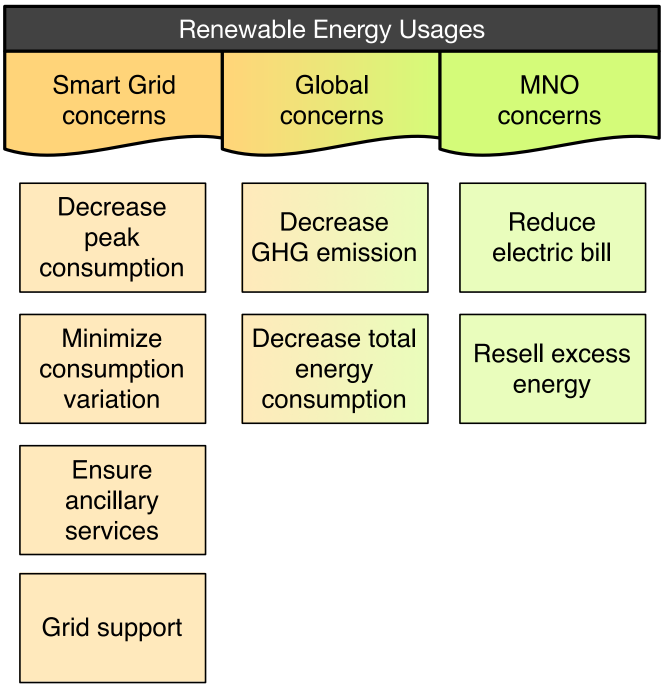

Figure 6.4: Classification of possible renewable energy usages in the proposed integration architecture.

consumption and increasing the utilization of renewable energy, but also taking into consideration the interaction with the SG.

As a result of this evolution, we classify the objectives of using renewable energy presented in Section 3.2.2 based on the concerns of the mobile network operator and the SG, see Figure 6.4. The existing studies consider the MNOs and global concerns [26, 74, 58]. However, replying to the Smart Grid concerns is open to many question and needs more attention.

6.4 Integrated Architecture

One of the characteristics of SG is integrating distributed energy sources, specifically renewable energy sources. This will facilitate the integration of BSs powered by renewable sources in the SG. Moreover, it is essential for MNOs to cooperate with the SG to achieve green communication and lower electric bill. The SG is also interested in cooperation with different consumers, especially high-energy prosumers such as renewable energy-powered mobile networks. In the following, we describe the mutual views between MNOs and the SG, and detail the elements of the proposed integration architecture.

6.4.1 How does the Smart Grid see the mobile network?

Different types of appliances will be connected to the SG from high-energy demand industry to small home appliances. Each of these appliances has special features, which affect the interaction with the SG. The mobile network can be considered as distributed loads, corresponding to geographically distributed base stations. The SG may also consider the mobile network as distributed energy provider when renewable energy sources and/or storages are implemented at the BS sites.

Washing machines are one of the home appliances that are expected to cooperate with the SG in the context of Smart Homes. It is predicted that *Smart Washing Machines* will dominates 23% of the smart appliances industry by 2015 [93]. We use the example of washing machine as an illustration to highlight the specific characteristics of a BS as an appliance in the SG.

Comparison between a washing machine and a mobile base station

Table 6.1 shows a comparison between a base station and a washing machine with respect to several criteria. The washing machine is characterized by finite-state energy demand depending on the on-going task. The energy demand of a base station is decomposed into two parts, static-and load-dependent. The static part is due to some components of the base station such as cooling, while the load-dependent part is variable and changes with the number of users and their conditions [60]. The power demand of a base station and a washing machine during a day are presented in Figure 6.5. The washing machine is used twice in this case. We notice that the power demand of a washing machine depends on the number of usages and the phase of the cycle. In each usage, the power demand consists of two phases: main cycle and end section.

Table 6.1: Comparison between a washing machine and a mobile base station.

Citeria \ Device	**Washing machine**	**Base station**
Energy demand pattern	Finite-state Machine based	Continuous
Service time	Few hours	Continuous service
Critical	No	Very critical
Consumption policy decider	Residents / Smart Grid	Mobile network operator
Actors	Residents	Multiple users + MNOs
Service accessibility	Private service	Open to all subscribers
Cooperation	With other home appliances	With other BSs and mobile users
Possible energy policy decision	Delay service	Switch-off, offload traffic, delaying users
Demand side management	Demand-Response or Direct-load-Control	Demand-Response

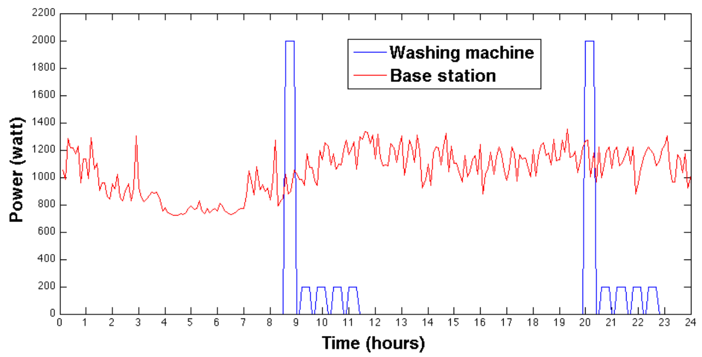

Figure 6.5: Power demand of a washing machine and a 3-sector base station during a day.

However, the power demand of a base station is dependent on the traffic and users' demand and varies through time.

The service time of a washing machine is limited to few hours, while mobile networks should ensure continuous service with maximum availability (99.999% of the time, known as five nines). The latter is not only essential for the satisfaction of users, but also due to the high criticality of telecommunication services. On the contrary, a temporal unavailability of washing service is tolerated. Washing machine in a Smart Home is accessible to its residents, which makes it a private service. Thus, residents represent the only actor and determine the amount and time of energy consumption. In contrast, the service provided by the network is open to all subscribers, which implies that multiple users contribute to the energy consumption of a base station.

In term of energy awareness, a washing machine may cooperate with other home appliances by delaying its service. A base station can work as a single entity or as part of system. In both cases, the base station can take the decision of consuming energy or storing it, if a local energy storage is present. As part of a system, a base station is capable of switching-off in some periods. Other actions can also be taken such as off-loading users to hot spots or delaying them, concept known by delay-tolerant users [94]. With respect to demand side management, demand-response and direct-load-control are both possible for the washing machine. However, this is not the case of base station since MNOs need to possess the decision of type and size of cooperation based on its commitments and traffic conditions, and thus only demand-response is possible in this case.

6.4.2 How does the mobile network see the Smart Grid?

Traditionally, mobile operators rely on the power grid as the main energy provider. However, the evolution of the power grid into smarter one and equipping BSs with renewable energy sources changes this narrow vision. The mobile network is no more passive. In addition to consuming energy from the grid, the mobile network can now sell renewable energy and provide several services to the grid. Moreover, the existence of energy storage can open new business models for the MNOs.

Moreover, the communication between entities of the SG is a key factor for achieving automation and interactivity. Mobile communications are one of the solutions to address QoS and reliability in data transmission [95] between the SG components. Moreover, one of the disruptive technology directions of 5G is to support M2M communications for massive number of connected devices with high link reliability, low latency and real time operation, a direction specifically suitable to the case of Smart Grid communication [96]. Therefore, SG may be a communication customer of mobile networks. However, this is not in the scope of our work. For more information about SG communication, see the exhaustive survey of Gao et al. in [97].

6.4.3 Proposed architecture

The previous perspectives verify the need for a new architecture to facilitate cooperation between mobile networks and the SG to increase their mutual benefits. On one hand, this architecture should take into consideration the special characteristics and needs of the mobile network. On the other hand, it should not affect the SG mechanisms or architecture. Our proposed architecture for integrating renewable energy-powered mobile networks and the Smart Grid is presented in Figure 6.6. The SG domain is not modified. Instead, the SG would have some special inclusions in their services to realize the BSs of mobile networks as special prosumers. This can be applied through a special algorithm embedded in the management system.

In the mobile network domain, the roles of some elements are updated and other logical and physical ones are added. This is minimal to achieve the desired cooperation. Moreover, the proposed architecture includes also the users in the decision of consuming energy.

Figure 6.7 introduces Renewable Energy-Aware Base Station model, which is used in the proposed integration architecture. This model is an extension to the renewable energy base station model we proposed in Section 2.4.1. In real scenarios, some base stations may not have local renewable sources. However, these base stations are aware of the grid's conditions and would contribute to the cooperation with the SG. We define these base stations as *Grid-Aware Base Stations*. In the following, we present the key elements of the proposed architecture.

Smart meters

Integrating appliances to the SG is usually done with the help of a Smart Meter. This meter is responsible of reading and transmitting its measurements, two-way communication between the meter and market participants (e.g. billing, energy-related services), support for various tariff models and payment systems, remote deactivation and start/finish of supply, etc. We should note that the smart meter does not control the decision of energy consumption in our proposed architecture.

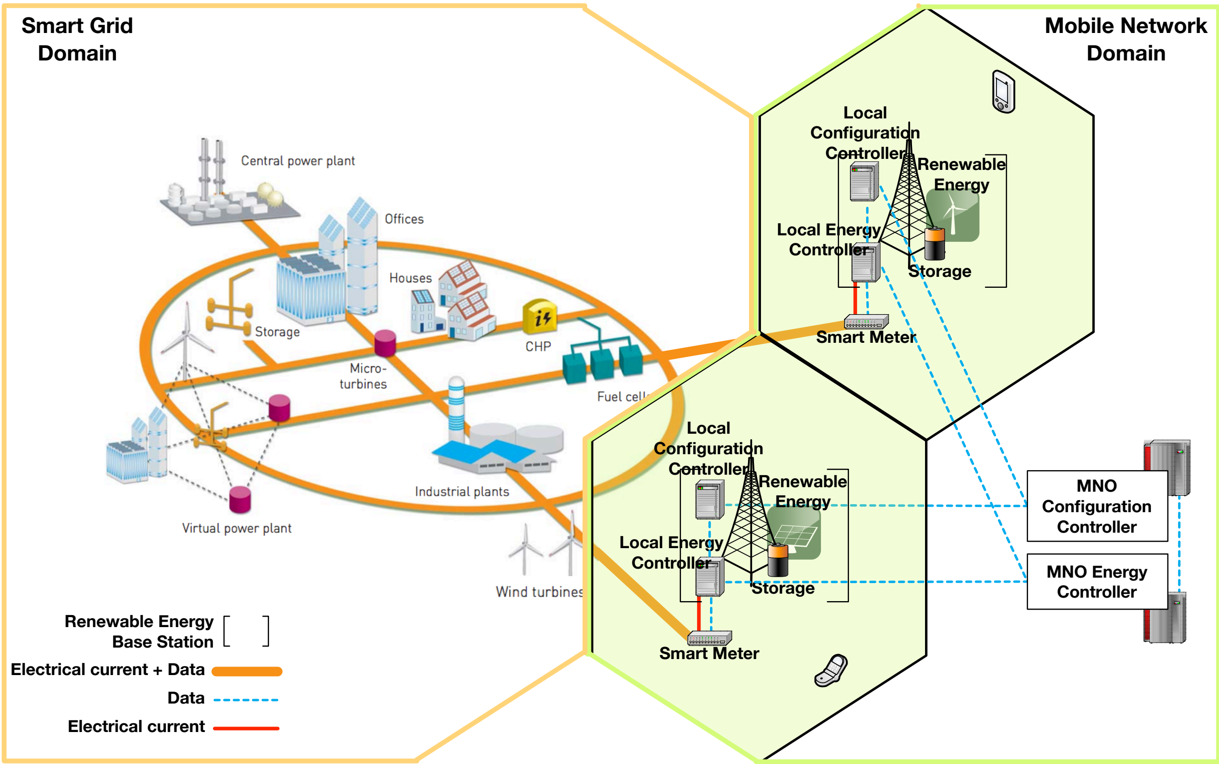

Figure 6.6: Smart Grid-Mobile Network integrated architecture.
The Smart Grid domain used in this figure is the architecture proposed by the European Commission in [98].

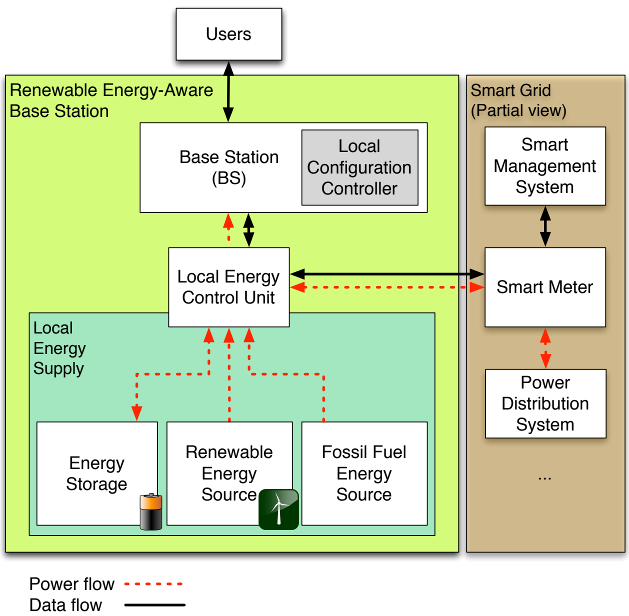

Figure 6.7: Renewable Energy-Aware Base Station model.

Local energy controller

The local energy controller (or local energy control unit) is an update of the power control unit presented in Section 2.4.1. In the proposed architecture, it is responsible of gathering information about the base station energy demand, renewable energy generation, storage and information provided by the SG, then sending it to the MNO energy controller. Also, it is responsible for executing the decision of energy consumption whether the decision is made locally or globally. The case of local decisions corresponds to a single operational base station, where the local energy controller takes the decision of using energy base on local information. In the case of global decision, the base station acts as a part of a system and the MNO energy controller sends the decision of using energy to be executed by the local energy controller.

This unit is also essential in supporting the grid. It may react fast, without getting back to the MNO energy controller, in case of urgent situations. For example, the local energy controller would inject energy from its local renewable sources and storage, depending on their states, instead of consuming on-grid energy in case of power drop.

MNO energy controller

The MNO energy controller is responsible of gathering the information sent by several local energy controllers and sharing them with the MNO configuration controller for taking the decision of energy usages and network configuration. Moreover, the MNO energy controller can be thought as an energy operatoror even an aggregator, which is described in Section 6.5 . It is also possible for this controller to perform other tasks, together with the local energy controllers and independent of the MNO configuration controller, such as buying and selling energy depending on the electricity price and the state of the energy storage at the base station site.

Local configuration controller

Satisfying the users is high priority consideration in mobile networks. The local configuration controller is responsible of gathering the information concerning the traffic and sending them to the MNO configuration controller for ensuring satisfaction of users. We can also see some other tasks concerning interaction with the users. For example, within high on-grid energy price, this unit is aware of the electricity price from the local energy controller and can notify the user that his call costs more. The user may then choose whether to continue the call or accept delaying it for some time, case of delay tolerant users [94, 99].

MNO configuration controller

This element receives information from different local configuration controllers. Then it adjusts the configuration of the network based on these information together with the MNO energy controller taking into account the MNO strategies. After taking the decision, the MNO configuration controller communicates with the local controllers. It should be noted that it is possible to find several MNO controllers (energy and configuration) within the network due to scalability and delay issues.

Users

In the proposed architecture, users do not only request services but also are part of the decision process. One of the examples is Delay Tolerant Users (DTU), which will allow the operator to manage the network in a more energy-efficient manner. In this type of service, the users are aware upfront about any forthcoming delays and are actively expressing their willingness to wait for their requests to be processed. Another example is time-based tariff plans, where the BSs would send periodically the price of the service taking into account the type and price of consumed energy. In general, the local configuration controller controls the interaction between the users and the base station.

6.5 Day ahead tariff and ancillary services

In Section 3.3.1, we presented the dynamic tariff programs provided by the power grid. Although dynamic tariff programs are often used by energy customers, it is possible for some customers to deal with the grid in another way, where energy prices follow day ahead tariff. This is possible when the power demand (or energy consumption) of the consumer is more than a certain threshold (e.g. consumers with peak demands greater than 1 MW [100]). In this case, energy can be purchased in advance and an auction is done day ahead to fix the hourly energy price for the next day.

Each day, the SG Transmission System Operator (or Independent System Operator) predicts the energy needed in the next day based on weather forecast, historical data and day ahead customers. Then, it organizes an auction between the providers, retailers and consumers to fix the electricity hourly price of the next day. Next day, additional trades are done to compensate the errors in the energy demand prediction. Among these trades, some are made in the last 15 to 30 minutes, and are known as *Ancillary*

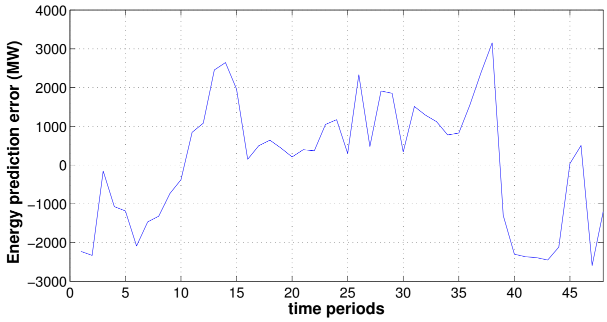

Figure 6.8: An example of the error between predicted and actual power demand in France [24].

Services [101, 102]. Figure 6.8 shows the prediction error for the power grid through a day in France.

Traditionally, ancillary services are provided by generators. Still, Controlling the load is considered as an important resource to the electricity industry [103, 101]. Any appliance that inherently has some storage in the process is a good candidate. The existence of energy storages at the base stations sites, and the new strategy to implement on-site RE sources promotes the mobile networks to be a suitable candidate in providing ancillary services. Moreover, the energy markets opened their doors for customers to participate in providing ancillary services. For example, Réseau de transport d électricité, France Electricity Transmission Network (RTE) proposes energy pools that deliver automated and continuous Demand Response on the French ancillary services, thus helping the grid to address short term imbalance. The framework has been launched in July 2014 [24].

The major challenge that faces customers willing to supply ancillary services is that the Smart Grid Operator (SGO) cannot deal with large number of individual resources and that the communications requirements would be overwhelming. These concerns are valid and are solved by aggregators [104, 105]. On one hand, aggregators handle the communications with a large number of loads. On the other hand, they represent single point of contact to the grid operator with significant amount of energy capacity, and this make the case similar to a large energy generator. Moreover, the Smart Grid operators are not interested in learning the details and concerns of each customer. Similarly, customers are in businesses of their own and have no time or interest in learning all about the Smart Grid. The aggregator can bridge this gap, creating a valuable resource in the process and this can be seen in Figure 6.9.

Figures 6.9 and 6.10 present the aggregator-based architecture and the protocol of message exchange between BSs, the Smart Grid and the aggregator. The aggregator

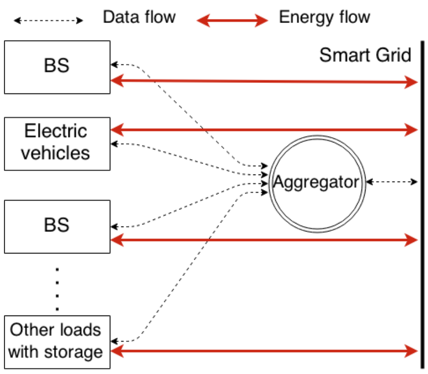

Figure 6.9: Aggregator-based architecture.

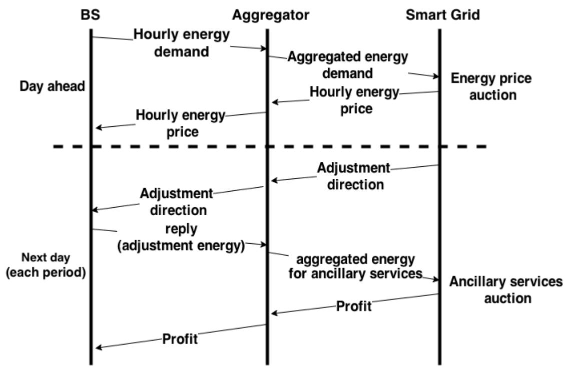

Figure 6.10: Messages exchange protocol.

can be the MNO energy controller for base stations only or an independent entity for different type of appliances such as in [105]. In Day ahead, the BSs provide the aggregator with its hourly energy demand. The aggregator participates in the energy price auction based on the information provided by all its customers and replies with the hourly price of energy.

Next day (adjustment day), the SGO periodically calculates the actual energy load and compares it to the predicted one. In case of lower actual energy load, the grid has excess energy. As some of the energy sources are uncontrollable (renewable energy sources) and others are slow-start ones (preferred not to be turned off), the grid asks its customers (willing to participate in ancillary services) to increase their consumption (adjustment *UP*). Conversely, the grid asks the customers to decrease their energy consumption (or provide energy) in case of higher actual energy load (adjustment *Down*), since turning on a new generator may need time and costs more. The profit of providing ancillary services is based on the participation power (amount of energy used in increase or decrease) and is calculated by an auction. If the BS did not participate in the adjustment it will not gain nor lose. However, a penalty is paid by the BS in case of violating the direction of adjustment (e.g. increasing its consumption when adjustment is down). It should be noted that the aggregator participates in all auctions on behalf of its customers.

It is worth noting that ancillary services markets are country-dependent and a review of these markets designs is available in [102]. Moreover, the terms adjustment *UP* and adjustment *Down* corresponds to regulation Down and regulation UP respectively in the Smart Grid nomenclature. Nevertheless, we will use the notation of adjustment for simplicity.

6.6 Delay Tolerant Users

Traditionally, BSs operate in an Always-ON paradigm and the access network is dimensioned to have enough capacity to support high traffic peaks. As the traffic varies in time and space, this approach consumes more energy than the needed to serve the actual traffic demand. Several techniques have been proposed in literature to reduce this energy wastage, e.g. sector/cell switching, cell breathing, heterogeneous deployments and relays [6].

A novel direction, combining some of the existing approaches with user demand management techniques, shows that further energy reductions are possible. In [99], the authors from our research team proposed the concept of DTU-aware strategies, in which a fraction of the users may witness an additional delay before accessing the network. The user flexibility allows to extend the periods of low energy consumption, e.g. when some sectors of a BS are not active, and results in reducing the overall energy consumption of the access network. These cooperative users are called delay tolerant users and the network propose them a maximal initial delay denoted by $delay_{max}$. As an extension of [99], we believe that the concept of DTU-aware strategies may also show advantages in the case where the MNO needs to reply to the Smart Gird requests for providing ancillary services and adjusting its energy load.

An example of the DTU-aware network reconfiguration strategies and its corresponding Markov model are presented in Figure 6.11 and 6.12 respectively. The model consists of a set of ergodic and homogeneous discrete-state Markov Chains to evaluate energy efficiency strategies based on dynamic resource adaptation. The system is modelled to be in one of two operational states, depending on the available radio resources. The system is in all-On state when all components of the access network are operational. In this state, the system has a capacity C_{max}. The system is in min-On state when only a fixed set of radio resources provides coverage and satisfies a minimum level of load. In this state, the system has a capacity $C_{min} < C_{max}$. When the system is in

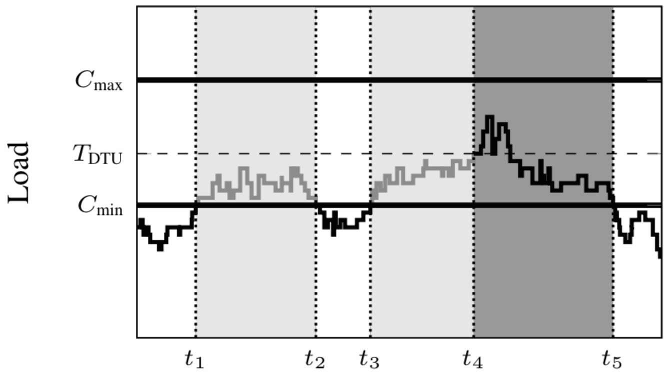

Figure 6.11: Load dynamic example of the DTU-aware network reconfiguration strategies [99].

White periods: system in min-On state, No delay. Light gray periods: system in min-On state, Delaying users. Dark gray periods: system in all-On state, No delay.

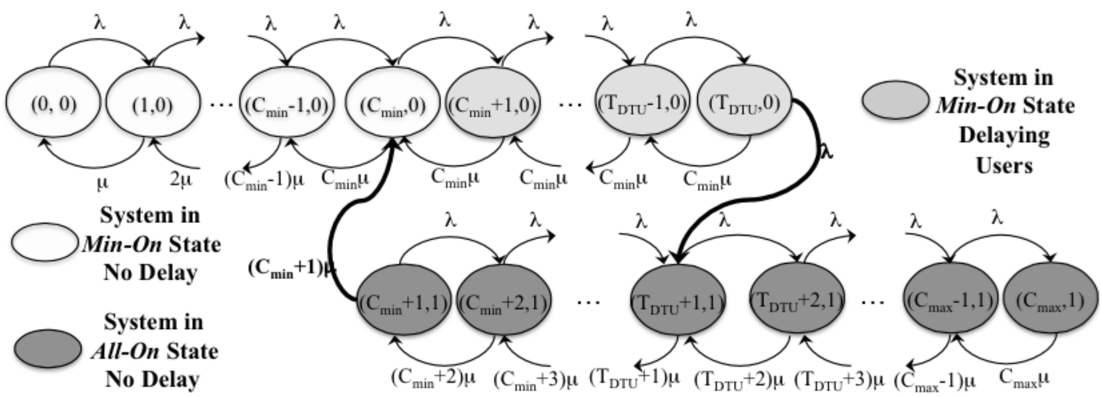

Figure 6.12: Markov chain of the user dynamic in the DTU-aware network reconfiguration strategies [99].

When T_{DTU} is equal to C_{min} (e.g. no light gray states), the Markov chain represents the dynamic of the traditional strategies.

min-On state and operating at its full capacity C_{min}, the start of new user services is delayed. Waiting users will be served when enough resources are available for them: either because some on-going services terminate, or because the system switches to all-on state and more resources made available. The system switches to all-On state when a threshold T_{dtu} in the number of waiting users is reached. Note that the selection of T_{dtu} is critical to ensure the service before $delay_{max}$. The system switches to min-On state when the load is inferior to C_{min}. The analysis of the model allows to estimate the average power consumption of the access network, the users waiting time distribution W as well as the blocking probability $Pr(block)$ of the users in the system using a DTU-aware strategy.

6.7 Problem formulation

We consider a base station powered by renewable energy and the Smart grid with enabled DTU capability. The generated RE may be directly used by the BS, stored and/or injected in the grid. The BS may also consume and store energy from the grid. Moreover, the BS operates in a distributed way without any cooperation with other BSs considering day ahead tariff and aim at providing ancillary services to the grid. The base station uses the generated renewable energy, storage management, dynamic resource adaptation and the concept of delay tolerant users to reply to the Smart Grid requests and provides it with ancillary services.

We consider a duration (one day) divided into p periods with duration T. The objective is to minimize the total energy operational cost of a BS in the described environment (providing ancillary services). Day ahead, the BS decides the hourly needed energy to be consumed from the grid in the next day. Next day, the decision of activating the DTU algorithm and the energy management is taken by the local configuration controller and the local energy controller at the beginning of each period to reply to the grid's requests. The decision at both stages (day ahead and in the adjustment day) are connected and the problem is formulated as follows:

$$minimize(\sum_{i=1}^{p} Cost_i) \tag{6.1}$$

subject to:

$$Pr(block_i) < \lambda_{block} \tag{6.2}$$

$$\sum_{i=1}^{P} DTU_i \leq \lambda_{dtu} \tag{6.3}$$

$$delay_i^{dtu} \leq delay_{max} \tag{6.4}$$

$$R_j \geq \lambda_R \quad \forall \quad j \in J \tag{6.5}$$

$$Pb_i \leq Pb_{max} \tag{6.6}$$

$$E_i \leq E_{max} \tag{6.7}$$

$$|Pstorage_i^{rate}| \leq P_{max}^{rate} \tag{6.8}$$

$$E_i^{cons} \leq E_i \tag{6.9}$$

Equation 6.1 presents the objective of minimizing the operational cost, where $Cost_i$ is the cost of electricity at period i. The cost is calculated as follows:

$$\begin{aligned} Cost_i = [(\max(P_i^g, 0) \times Price_i) - (P_i^{adj} \times Price_i^{adj}) \times x_i + \\ (P_i^{viol} \times Penalty_i^{viol}) \times y_i] \times T \end{aligned} \tag{6.10}$$

where P_i^g is the power taken from the grid, P_i^g may be negative in case of injecting energy to the grid. $Price_i$ is the price of grid energy, P_i^{adj} is the adjustment power $P_i^{adj} = |P_i^d - P_i^g|$ where P_i^d is the power demand sent by the BS in the previous day, $Price_i^{adj}$ is the gain due to participating in adjustment, x_i is 1 if the BS participates in the adjustment and 0 if not, P_i^{viol} is the power difference when opposing the adjustment direction and is given by $P_i^{viol} = |P_i^g - P_i^d|$. $Penalty_i^{viol}$ is the penalty of opposing the adjustment direction, y_i is 1 if the BS opposes the adjustment direction and 0 if not. It should be noted that we mean by opposition the fact of decreasing the energy load in case of Up direction and increasing the energy load in case of Down direction.

Equations 6.2 to 6.9 are valid for all $i \in [1, p]$. They represent the problem's constraints. Equation 6.2 states that the probability of blocking a user $Pr(block_i)$ is less than a threshold λ_{block}. Equation 6.3 limits the duration in which the DTU-aware algorithm is activated, where DTU_i is 1 when DTU algorithm is activated and 0 if not. λ_{dtu} is the maximum number of periods for activating the DTU algorithm. Equation 6.4 states that the maximum allowed delay for a service is $delay_{max}$. Equation 6.5 grantees that all users obtain a minimum bit rate R_j, where J is the set of all users. Equation 6.6 is a system constraint that states that the power of a BS Pb_i is limited by Pb_{max}. This limitation is due to design of the BS components and is related to the maximum transmitted power P_{max}. Pb_i depends on the operation of the BS, i.e. if the DTU-aware algorithm is activated or not. Equation 6.7 states that the amount of stored energy E_i is less than than the maximum capacity of the storage E_{max}. Equation 6.8 states that the charging/ discharging rate $Pstorage_i^{rate}$ is less than the threshold P_{max}^{rate}. This constraint is essential for the performance and life time of the storage. Finally, Equation 6.9 limits the energy used from the storage E_i^{cons} to the stored energy E_i.

6.7.1 Optimizing DTU-aware algorithm

We consider that the base station is able to use the DTU-aware algorithm proposed in [99], which model was described in Section 6.6. We are interested in the BS configuration providing the larger reductions in terms of power consumption when the DTU-aware algorithm is activated. Thus, we consider a BS using an adaptive transceiver chain capable to switch between one active sector (when in min-On state) and three active sectors (when in all-On state) [106].

The power consumption in each of this system states is calculated based on EARTH power model. Information about the BS dimensioning for the DTU-aware algorithm is given in Table 6.2. For each offered load and maximal tolerable delay proposed to the

Table 6.2: System parameters.

Deployment	
Deployment type	Urban Macro
Site area [km^2]	0.2165
BS type	3-sector Reconfigurable
Transmission bandwidth [MHz]	10
Antenna configuration	$2x2$ MIMO
Total resource blocks	50
Power consumption	
number of transceivers	2 or 6
Traffic characteristics	
System capacity [Mbps/km2]	115
Session target throughput [kbps]	500
BS session capacity when all-on (C_{max})	30
BS session capacity when min-on (C_{min})	10
Session duration [s] (μ^{-1})	81
λ_{block}	0.05
$delay_{max}$ [sec]	10
Maximum duration of DTU	4 hours (8 periods)
Power system	
Type	Premium Solar panels
Maximum power [kW]	4
Solar panel efficiency	19%
Generated energy [% of BS demand]	33
Storage capacity E_{max} [kWh]	4
Storage efficiency E_{eff}	90%

users ($delay_{max}$), the threshold minimizing the BS power consumption Pb_i in a given period is computed by using exhaustive search.

The optimal results for the considered BS are presented in Figure 6.13 depending on the offered load and $delay_{max}$. In this figure we can see the power reduction achieved for the DTU-aware algorithm regarding an always-ON BS, i.e. a BS working all the time with three active sectors. In the rest of the document, we consider that when the DTU-aware algorithm is not active, the BS is working in an always-ON regimen. When the DTU-aware algorithm is activated, the power consumption depends on the given gain resulting on the application of the algorithm for the afforded offered load.

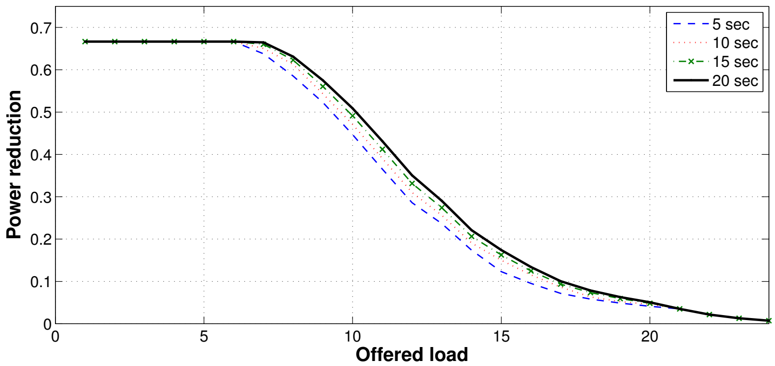

Figure 6.13: Power reduction as function of offered load for different maximum delays ($delay_{max}$).

Moreover, we will consider small delays proposed to the users, configuring the DTU-aware algorithm with $delay_{max}$ not longer than 10 seconds.

6.8 Proposed algorithm

The problem is highly complicated, where the decision of sending the hourly energy demand (day ahead stage) of the BS to the aggregator depends on many parameters that include but are not limited to the time of the day, weather, RE generation, grid load itself depend on many factors, traffic load, historical data of the grid, etc. Then, the BS has to determine the decisions of activating the DTU-aware algorithm and determining the amount of energy consumed or stored from the grid as a reply for the grid request at each period of the next day stage. The decision at each period also depends on the day ahead stage decision and the decisions at the previous periods (of the next day stage). In the following we present our algorithm proposed in [107].

In order to reduce the complexity of the problem, the BS sends the hourly needed energy without considering RE or the DTU-aware algorithm. It is also possible to send the maximum power demand. This will greatly facilitate the problem for the MNOs as it will separate the two stages decisions. The decision at each period will be based on the adjustment direction and conditions at each period. Algorithms 3 and 4 present the behaviour of the BS when the adjustment is Down and Up respectively.

Algorithm 3 determines the power taken from the grid P_i^g. The BS first activates the DTU-aware algorithm if the power reduction due to its activation R_{DTU} is more than a threshold R_{DTU}^{min}, RE is not available and the duration for which the DTU-aware algorithm was activated, $Duration_i^{DTU}$, is less than a threshold λ_{DTU}. Then,

Algorithm 3 Adjustment Down.

Inputs: storage state S_i, power of RE source P_i^{RE}, traffic load TL_i, BS power demand Pb_i, maximum injecting power P_{max}^{inj}

Outputs: DTU setting, power from SG P_i^g

if ($R_{DTU}(TL_i) \geq R_{DTU}^{min}$) and ($Duration_i^{DTU} < \lambda_{DTU}$) and ($P_i^{RE} = 0$) **then**

  Set DTU active

end if

if S_i is low **then**

  if RE is available **then**

    Use RE and storage to maximum reduction of grid energy

    $P_i^g = \max(0, Pb_i - E_i/T - P_i^{RE})$

  else

    case DTU is active: $P_i^g = Pb_i \times R_{DTU}(TL_i)$ // reduction is only due to DTU

    case DTU is inactive: $P_i^g = \alpha \times Pb_i$ // Reduce portion of grid energy by using the storage

  end if

else if S_i is medium **then**

  if RE is available **then** Inject energy to the grid

    case DTU is active: $P_i^g = -P_{max}^{inj}/2$

    case DTU is inactive: $P_i^g = -P_{max}^{inj}/4$

  else

    $P_i^g = 0$ // use storage to achieve zero grid energy

  end if

else

  S_i is high //Inject energy to the grid

  if RE is available **then**

    case DTU is active: $P_i^g = -P_{max}^{inj}$

    case DTU is inactive:$P_i^g = -3 \times P_{max}^{inj}/4$

  else

    case DTU is active:$P_i^g = -P_{max}^{inj}/2$

    case DTU is inactive:$P_i^g = -P_{max}^{inj}/4$

  end if

end if

the algorithm determines the power from the grid P_i^g considering the state of the DTU-aware algorithm (active or not), storage state S and availability of RE. In case of injecting energy to the grid, P_i^g is negative and the injecting power is in terms of a pre-determined value denoted as maximum injecting power P_{max}^{inj}. When P_i^g is less than the BS demand, power is taken first from generated RE (if available) and then from the storage. If the DTU-aware algorithm is not activated, RE is not available and the storage is depleted, P_i^g would be equal to the power sent in the previous day, and thus no adjustment violation can occur during adjustment Down.

When the adjustment is Up, Algorithm 4 determines how much the storage is charged, translated into P_i^{charge}. P_i^{charge} depends on the storage state S_i and is limited by the availability of the storage (maximum capacity). The charging rate is given in terms of a pre-defined value P_H^{charge}. The power taken form the grid depends on the decision of the algorithm, generated RE, storage state and the demand of BS. The power taken from the grid is given by $P_i^g = max(0, min((E_{max} - E_i)/T, P_i^{charge}) + Pb_i - P_{RE})$, where E_{max} is the maximum capacity of the storage, E_i is the storage state at the beginning of the period, Pb_i is the power of the BS and P_{RE} is the power generated by RE source. P_i^g may be less than the demand sent in the day ahead stage, such as when RE is available and storage is fully charged. In this case, RE is used to power the BS and the adjustment direction is violated. It should be noted that generated RE is prioritized over grid energy (taken from RE then from grid). Although, this would result in violating the direction in some cases, but it avoids wastage of generated RE. Note that P_{max}^{inj} and P_H^{charge} should be carefully chosen such that the constraint in Equation 6.8 is respected.

Algorithm 4 Adjustment Up.

Inputs: storage state S_i, P_H^{charge}
Outputs: charging power of the storage P_i^{charge}
  if S_i is low **then**
    Charge S with $P_i^{charge} = P_H^{charge}$
  else if S_i is medium **then**
    Charge S with $P_i^{charge} = P_H^{charge}/2$
  else
    Charge S with
  $P_i^{charge} = min((E_{max} - E_i)/T, P_H^{charge}/4)$
  end if

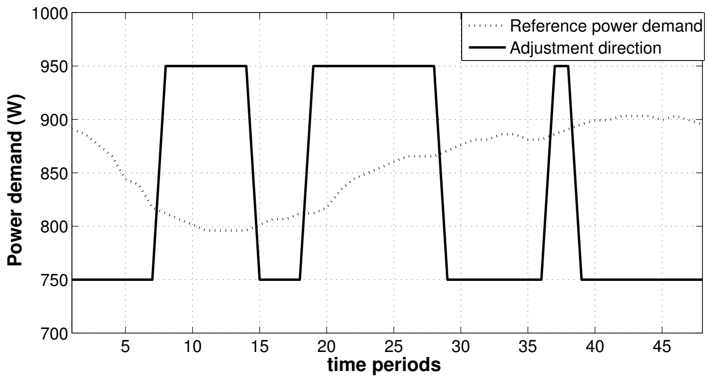

Figure 6.14: An example of the Smart Grid request direction through a day in France.

6.9 Simulations and results

We consider solar panels as the renewable energy sources. The intermittency of RE generation is taken into consideration as small variations in the production due to temporary conditions (clouds for example). The parameters of the system are presented in Table 6.2. The studied duration is one day divided into 48 periods of duration $T = 30 \quad min$. Three algorithms were simulated: 1) Traditional 2) SPAEMA (Section 3.3.2) 3) proposed algorithm. The reference consumption corresponds to the normal operation (Always-On) of the BS without using RE or any energy efficiency technique. For reference consumption, traditional and SPAEMA algorithms, the energy costs are calculated based on the real time price of electricity provided by the grid [91]. The reference consumption is also sent in the day ahead consumption. The price of electricity, adjustment direction, average adjustment gain and the violation penalty at each period are provided by the French power grid [91, 24] to simulate the proposed algorithm. These data are used to calculate the energy cost and the profit of providing ancillary services at each period. Simulations are done for several energy prices and adjustment sequences.

Figure 6.14 presents one of the simulated sequences of the Smart Grid request direction and the reference power of a base station, for which we will show later the behaviour of the base station. The curve representing the adjustment direction gives only the direction of adjustment without any further meaning for its value, i.e. it indicates adjustment Up or Down if it is above or below the reference consumption curve respectively. We should note that the quantitative results, presented later, are the average of many simulations done for different sequences of Smart Grid requests, renewable energy generation, energy prices and adjustment gain prices.

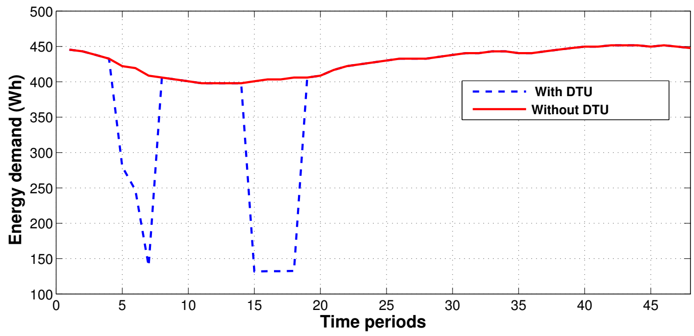

Figure 6.15: Effect of activating DTU-aware algorithm on the energy demand of the BS.

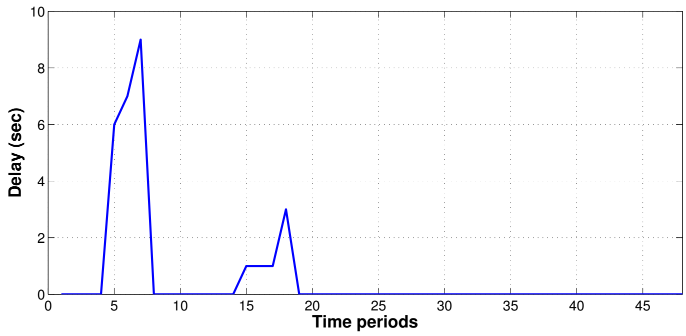

Figure 6.16: Maximum delay of service.

Figure 6.15 presents the BS energy demand with and without using the DTU-aware algorithm. The proposed algorithm activates the DTU-aware algorithm for total duration of 7 periods (3.5 hours), and leads to 9.1% of energy reduction. The DTU-aware algorithm succeeds in compensating the unavailability of RE in some periods to support the BS in providing ancillary services. This comes with limited price in terms of delaying the users, where Figure 6.16 shows the maximum delay that might be experienced by the user with respect to time. The maximum delay that a user may experience is 9 second. Moreover, 7.1% of the users may experience small delays. Similar results appears for other sequences of ancillary service requests.

The grid energy consumption of the BS for the simulated algorithms are presented in Figure 6.17. The figure shows that the proposed algorithm succeeds to follow the adjustment direction more than 83% of the day. The remaining duration is divided into two types. The BS could not decrease the energy consumption in the beginning of the day due to the unavailability of the storage (no stored energy) and the RE and limited effect of DTU. In this type, the BS pays only the cost of purchased on-grid energy based on the auction price. In the second type (periods 24 to 28), the grid asks the BS to increase its consumption. However, the BS violates the adjustment direction

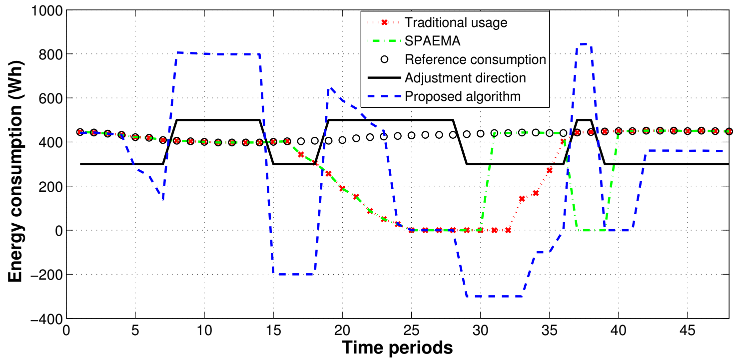

Figure 6.17: Grid energy consumption of the simulated algorithms.

Table 6.3: Energy operational cost (%) of simulated algorithms with respect to the reference scenario.

Traditional	SPAEMA	Proposed
64.8	59	-27

and decreases its consumption. This is due to high generation of RE and unavailability of the storage (fully charged) in this period. In this case, the BS pays a penalty to the SG.

The traditional algorithm and SPAEMA consume on-grid energy at the beginning of the day when RE is unavailable. Then, both algorithms starts to consume RE instead of on-grid energy when RE is available. However, SPAEMA stores some energy when the price decrease to be used later at higher on-grid energy prices. The behaviour of the proposed algorithm is different, as it follows the adjustment directions. At the beginning of the day, the proposed algorithm stores grid energy at the Up adjustment to be used later at down adjustment when RE is not available. Also we find that the proposed algorithm results in negative on-grid energy (e.g. period 30). This is the case where the BS injects energy into the grid. Moreover, we record a special performance of the proposed algorithm in the periods from 36 to 39, where the proposed algorithm acts in a contrary way to SPAEMA, i.e. opposite to the intuitive price-energy consumption relation. The BS increases the grid energy consumption despite that the price of energy increases to the high range in this period, while SPAEMA decrease its on-grid energy consumption. This behaviour is related to the global behaviour of the grid. These periods represent the start of the grid peak, where new generators are started to match the highest demand of the peak. Excess energy is available and the grid asks the customers to increase their energy load as it costs a lot more to stop some generators or restart them.

Table 6.3 represents the energy operational cost of the simulated algorithms for a day with respect to the reference scenario. SPAEMA achieves 41% of energy cost reduction and outperforms the traditional (35.2%) and the proposed algorithm (37%). Nevertheless, the proposed algorithm achieves profit equal to 90% of the initial electric bill (reference consumption) leading to negative operational cost, i.e. the grid will pay to the MNO.

6.10 Conclusion

In this chapter, we described the main characteristics of the Smart Grid and explained the evolution of energy management concepts after introducing renewable energy sources for powering mobile base stations and considering the Smart Grid environment. Moreover, we proposed a new integration architecture for mobile networks and the Smart Grid to facilitate the interaction between them. As an application of this architecture, we studied a new behaviour of base stations powered by renewable energy in the Smart Grid environment, where base stations provide the grid with ancillary services. We introduced the concept of providing ancillary services and justified the suitability of mobile networks as relevant candidates. After defining the system model and explaining the concept of delay tolerant users, we proposed a new formulation of the problem as minimizing the energy operational cost. We proposed a heuristic algorithm to answer the grid requests by managing generated renewable energy, energy storage, radio resources and activation of delay tolerant users. Results showed that this approach achieve negative operational cost.

CHAPTER 7 Conclusions and Perspectives

7.1 Conclusions

In this thesis, we studied cellular networks powered by renewable energy sources and the power grid. In Chapter 2, we surveyed the existing work in the context of cellular networks powered by renewable energy sources. Inspired by the state of art, we proposed a new model for renewable energy-powered base stations and detailed its components that should be modelled in order to correctly analyze the behaviour of such base stations. Moreover, we proposed a classification for the existing literature, where we highlighted the main tools and challenges in each research sector. Following this classification, we integrated the tools and algorithms used in operating on-grid and off-grid base stations in a framework model, where the interaction between the energy efficiency and renewable energy layers allows better utilization of renewable energy. Concluding this chapter, we identified several aspects in which the problematic of cellular networks powered by renewable energy and the power grid (on-grid cellular networks) needs more investigation.

Consequently, we proposed a new methodology to identify the case studies of on-grid cellular networks powered by renewable energy in Chapter 3. We presented some of the objectives of using RE in powering cellular base stations that are found in literature and proposed several new ones. This widened the scope of dealing with renewable energy in powering on-grid base stations, as most of the studies deal with minimizing the on-grid energy consumption. We identified the constraints that may appear while solving the problem. Moreover, we presented the main existing dynamic tariff programs proposed by the power grid. Considering dynamic tariff is essential when adopting the objective of reducing the energy operational cost since reducing the energy consumption and energy cost are not identical when the price of energy varies through the day. We considered a network of base stations operating in a variable energy price environment.

We assumed that each base station operates individually by taking the decision of using renewable energy. This approach has the advantage of distributed operation of base stations without the need for any information exchange between them. We proposed a simple yet efficient energy management algorithm (SPEAMA) that determines the usage of renewable energy based on energy price and storage levels. Results verify the effectiveness of the proposed algorithm, where we showed that the proposed algorithm achieves lower on-grid consumption but higher cost reduction compared to traditional greedy algorithm. On one hand, this validates that the objectives of reducing the on-grid energy and energy operational cost are different. On the other hand, the importance of a good energy management is verified when using renewable energy in powering on-grid base stations.

Our first work did not take into consideration possible cooperation between base stations. Thus, in Chapter 4, we considered the problem of reducing the energy operational cost of a network of macro- base stations. The network can adjust its parameters by allocating and re-allocating renewable energy, switching-off base stations, adjusting the transmitted power and determining the number of active resource blocks in a base station. We started by presenting the problem formulation of minimizing the energy operational cost of a network. We decompose the problem into 3 sub-problems: renewable energy allocation, energy consumption minimization and radio resource allocation. To the best of our knowledge, we are the first to propose the need for a definition of renewable energy utilization and to identify that this definition depends on the chosen objective(s), which is reflected in the problem formulation of renewable energy allocation. We have proposed a new algorithm that allocates and reallocates renewable energy, switches-off base stations, adjusts the transmitting power of base stations and determines the number of active resource blocks of each base station. The latter is of great importance, as different cell sizes (and consequently different traffic loads) are obtained at each base station depending on its renewable energy availability and allocation. The simulation results show the effectiveness of cooperation between base stations as significant cost reduction is obtained when cooperation is done in comparison with the non cooperative case for the same amount of generated renewable energy. Moreover, results show that the proposed algorithm can achieve significant cost reduction by using even small amounts of renewable energy. Furthermore, we also studied the effect of deploying small cells powered solely by renewable energy, where the simulation results show further cost reduction.

The previous conclusions in dealing with renewable energy powered on-grid network were based on simulations. In Chapter 5, we analyzed the usage of renewable energy in a realistic environment. Based on real measurements of a major European mobile network operator, we evaluated the effect of renewable energy allocation and base station switch-off in terms of on-grid energy saving and energy cost reduction. Adjusting the transmitting power of BSs was not used, since the operator considers it risky as it may have undesired effect on the interference level in the network. After analyzing the coverage and capacity of the network, we proposed two switch-off algorithms that aim at reducing the energy consumption and energy cost respectively. Switching-off base stations are constrained with coverage and capacity constraints to avoid the degradation of users quality of service. We were able to achieve 18.69% reduction of energy consumption. Moreover, we proposed some recommendation regarding the process of dimensioning (sizing) renewable energy sources and energy storages. Following these recommendation, we found that it is possible to decrease up of to 51% of the electric bill by using renewable energy sources that produce only 20% of the network energy demand.

To complete the set of contributions provided in this thesis, in Chapter 6 we introduced the evolution of energy management concept from *energy efficiency* to *Smart Grid aware*. We presented the definition of the Smart Grid and the main improvement in comparison to the traditional power grid. Moreover, we answered two questions to understand how cellular networks should deal with the Smart Grid: 1) How does the Smart Grid see the mobile network? 2) How does the mobile network see the Smart Grid? We highlighted the energy characteristics of a base station by a detailed comparison with typical home appliance. This allowed us to propose a new integration architecture of cellular networks and the Smart Grid, which facilitates the interaction between them. Afterwards, we studied a novel energy behavior of a base station, where it provides ancillary services to the Smart Grid. To the best of our knowledge, we are the first to propose this concept in the operation of base stations. We used the storage and generated renewable energy and exploited the concept of delay tolerant users to increase or decrease the on-grid energy consumption based on real-time Smart Grid requests. We proposed an aggregator based architecture and a message exchange protocol between the base stations and the Smart Grid. We presented the problem formulation, where the aim is also to reduce the energy operational cost. Solving the high complexity of the problem, we proposed a heuristic algorithm to operate the base station. The algorithm manages the energy and the delay tolerant users activation policies. Results show that providing ancillary services does not only support the Smart Grid but may also lead to negative energy operational cost for network operators (i.e. return gain to the network operator).

7.2 Future work

The work we have done in this thesis can be considered as a step towards the seamless integration of renewable energy sources into the future generations of cellular networks. Throughout our work, we found that there are many more opportunities to be explored. We have already identified different research directions and their challenges in Chapter 2. More-specifically, our work was focused on operating cellular networks powered by renewable energy and the power grid. Next, we state some of the ideas and perspectives that we consider a natural extension of the results presented in this thesis.

One of the perspectives is to consider data delay while turning-off or adjusting the transmitted power of base stations. When base stations switch-off (or cell size shrinks), their loads are transferred to other base stations. This will increase the delay of the recipient base stations due to the load increase. Thus, the trade-off between any of the possible objectives (energy reduction, cost reduction) and delay is to be investigated.

Moreover, our results concerning the addition of small cells encourage the investigation of heterogeneous network powered by renewable energy sources. Some researchers already started to work in this direction [77, 51]. However, considering heterogeneous networks for reducing the energy operational cost or providing services to the power grid still needs more investigation.

Another interesting idea is to consider prediction of renewable energy and to include learning in the process of renewable energy allocation and energy management. This can be done by using tools of machine learning or artificial intelligence.

Moreover, we have concluded in Chapter 5 that advance sizing of renewable energy sources and energy storages is a promising technique to avoid high investment cost and reducing the energy operational cost at the same time. However, our work does not explicitly consider dimensioning techniques. Another possible extension is to design an effective technique that determines the size of renewable energy sources and the energy storage while taking into account network operation.

One of the high priority tasks in our on-going research is to deepen the work done in Chapter 6. Our aim is to design a model for the behavior of base stations when providing services to the grid.

To further exploit the potential of using renewable energy in powering base stations, the mobile network operators should start considering new architectures, such as the one we proposed in Chapter 6, and new strategies, such as providing ancillary services. Moreover, the access network should become highly dynamic to adopt to the availability of renewable energy and variations in the Smart Grid conditions. Furthermore, including the users in the decision process is promising to contribute in reducing the energy cost and Carbon footprint, such as accepting the delay tolerant users strategies in operating the network.

Powering base station by renewable energy sources does not only contribute in reducing the operational cost and carbon emissions, but can also facilitate the upgrade of existing operators to next generation networks and would support new business models. For example, a new trend in spectrum regulation for mobile broadband access is to license spectrum to new operators subject to power and/or environmental constraints. Moreover, mobile operators would add small cells powered by renewable energy sources to improve the network capacity and reduce the energy cost, thus supporting their existing business model and reducing their operational cost.

A further contribution to the operating of cellular networks is coupling with the Smart Grid. On one hand, the cellular networks are major energy consumers. On the other hand, the Smart Grid would use cellular networks for communication between its entities. The smart grid would have some special inclusions in their services to realize the specificity of base stations that communicate urgent messages, thus ensuring stable operation of the Smart Grid.

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Résumé

L'Internet est l'une des principales infrastructures créées dans les dernières années. Avec sa popularité croissante, l'empreinte énergétique d'Internet devient un facteur important à considérer. Une des façons les plus fréquentes d'accès à l'Internet se fait via la communication sans fil cellulaire, qui consomme plus de 0,5% de l'approvisionnement mondial en énergie. Ce pourcentage augmentera encore plus avec la croissance drastique de la demande des usagers. Tenant compte du fait que les stations de base sont le consommateur majeur de l'énergie, leur alimentation avec des sources d'énergie renouvelable a le potentiel de devenir un outil indispensable pour les opérateurs de réseaux mobiles. Il est donc important d'étudier le sujet afin de déterminer les gains potentiels, les scénarios d'applicabilité, les stratégies de déploiement et des nouvelles architectures de système.

Dans le secteur de l'énergie, des efforts importants ont été dépensés pour l'évolution du réseau électrique en un réseau plus intelligent, la Smart Grid. Avec les fonctionnalités avancées de Smart Grid, il est obligatoire qu'elle soit considérée en étudiant le comportement énergétique des réseaux mobiles liés au réseau électrique. Cette thèse vise à contribuer dans le domaine des techniques dans les réseaux mobiles alimentés par des sources d'énergie renouvelables et par le réseau électrique du type Smart Grid.

Mots-clés : Réseaux cellulaires, Gestion des ressources radio, Smart Grid, Energie renouvelable, Gestion de l'énergie, Architecture du système, Durabilité énergétique, Efficacité énergétique

Abstract

The Internet is one of the largest infrastructures created in recent years. With its growing popularity, its energy footprint becomes an important factor. One of the most frequent ways Internet access is via cellular wireless communication, which consumes more than 0.5% of the global energy supply. This percentage will increase more with the dramatic growth in user demand. Taking into account that the base stations are major consumers of energy, powering them with renewable energy sources has the potential to become an indispensable tool for mobile network operators. It is therefore important to study the subject in order to determine the potential gains, the applicability scenarios, deployment strategies and new system architectures.

In the energy sector, significant efforts have been spent on the development of the power grid into smarter one, the Smart Grid. With the advancements in Smart Grid functionality, it is mandatory to be considered when studying the energy behavior of mobile networks that are connected to the grid. This thesis aims to contribute in the field of techniques used by mobile networks that are powered by renewable energy and the Smart Grid.

Keywords : Cellular networks, Radio resource management, Smart Grid, Renewable energy, Energy management, System architecture, Energy sustainability, Energy efficiency

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